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Modeling Sugarbeet Quality Variables from Satellite Images and Canopy Spectral Indices

Subodh Kulkarni
South Dakota State University

MODELING SUGARBEET QUALITY VARIABLES FROM SATELLITE IMAGES AND CANOPY SPECTRAL INDICES

BY

SUBODH KULKARNI

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This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science degree and is acceptable for meeting the thesis requirement for this degree. Acceptance of this thesis does not imply that conclusions reached by the candidate are necessarily the conclusions of the major department.

Dr. Daniel Humburg, Associate Professor — Date
Thesis Advisor and Major Advisor

Dr. Van Kelley, Associate Professor — Date
Head, Department of Agriculture Engineering

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Dedicated to,

Dr. Timothy Wittig

ABSTRACT

MODELING SUGARBEET QUALITY VARIABLES FROM SATELLITE IMAGES AND CANOPY SPECTRAL INDICES

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Remote sensing was used to model crop quality from measurements of canopy spectra. Three indices of canopy characteristics, derived from satellite image data, were tested for relationship to whole-field sugarbeet quality. Quality was quantified as recoverable sucrose per ton of harvested sugarbeets. Quality data were extracted from the year 2002 Field Database of the Southern Minnesota Beet Sugar Co-operative, (SMBSC), Renville, Minnesota. Linear regression models utilizing canopy indices and changes in canopy indices over time were tested for relationship to sugarbeet quality for four classes of sugarbeets. Classes of sugarbeet tested represented fields planted to a mix of varieties resistant to the disease rhizomania, conventional varieties, and two pure strains. Linear regression models using individual indices for the fields planted to mixed conventional varieties and to a pure strain, B4811, showed statistical significance. Models using temporal changes in individual indices also showed statistical correlation. The trends of regression lines were meaningful in understanding variation of sugarbeet harvest quality with changes in canopy indices on two different single dates. Multiple linear regression models utilizing changes in individual indices over different time intervals also indicated significant correlations for a mixed conventional class and the B4811 variety. The trends in indices over time suggest that fields showing greater decline in indices can be classified as having higher recoverable sucrose content. The study suggests remotely sensed canopy spectral variations using satellite images, and sugarbeet quality variation may be used to develop models to relate quality to canopy indices. However, a larger sample size may be necessary, and additional information regarding fields with pronounced disease or population problems will be necessary to minimize scatter in the data used to develop models.

Keywords: Sugarbeet, Remote Sensing, Vegetation Indices, Canopy, Site Specific Crop Management.

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Chapter 1. Introduction

Agriculture has become an integrated enterprise that brings together farmers, agriculturists, engineers, technologists and industrialists. Farming practices, existing for decades, are being modified towards something called precision farming.

Traditional field management considers the whole field for an input such as a fertilizer or pesticide application, whereas precision farming treats a subset of the field based on the requirements or characteristics of the local area. To understand the needs of such areas it is necessary to have information. Modern information technologies provide the platform to gather multiple data types, and process and analyze them. The large amount of data potentially collected to describe attributes over fields can be used for soil mapping, yield monitoring, weed and pest detection, fertilizer applications and deciding on the priorities of harvest to manage resources and utilize them economically.

Precision farming owes its existence to a combination of advancements in global positioning systems (GPS), geographic information systems (GIS), and application controllers which enable a farmer to assess field conditions, and apply inputs to help obtain improved yield results. This type of farming practice is also known by the term "Site-Specific Crop Management". It is a management strategy that uses information technologies to bring data from multiple sources to bear on decisions associated with crop production (National Research Council, 1997). Site-specific crop management can be applied to agriculture in a variety of ways from pre-planting operations to harvest. Geographic information systems and remote sensing provide a systematic approach to manage the large amounts of data collected and accumulated, along with some of the tools necessary for analysis and interpretation.

Remote sensing is an associated technology of site-specific crop management and is emerging as a very powerful tool for studying land cover. It is now becoming one of the integral parts for assessing the status of the growing crop.

1.1 Yield Monitoring and Mapping Systems

Spatial distribution of yield at harvest can be mapped to understand variability of crop production with respect to location within the field. There are many ways to measure crop yield. In harvest of grain crops, batch-type yield monitors measure the grain in the tank of the combine by weight, whereas instantaneous yield monitors measure and record yield continuously as the combine travels across the field. Most recent systems record each data point of associated yield and geographic position using the GPS. Some yield systems measure crop-volume, and other systems weigh the crop or determine mass flow rate.

Walter et al. (1995), described development of a sugarbeet yield measurement technique. They measured mass-flow-rate using load measuring idler wheels or supports under the crop conveyor on harvesters (Benjamin, 2002). Hall et al. (1997) employed a 3 Hz. low pass filter on a system that sampled the weight of sugarbeets on a harvester conveyer at 25 Hz. A 50-point moving average was used to smooth the data to provide a measure of harvest flow rate. In later work they put a torque sensor and two sets of load cells on a sugarbeet harvester. The torque sensor was mounted in the scrub chain driveline. This driveline is a scrub conveyer driving system, which is at the rear of the sugarbeet harvester. One set of load cells was mounted at the discharge of the scrub chain. A second set of load cells was mounted at the end of elevator. Using this system they obtained real time yield data continuously while harvesting sugarbeets.

Yield mapping systems are used to produce yield maps based on instantaneous yield measurements at coordinate locations. The variability of the yield in the field can be easily visualized and the farmer can investigate results of treatments applied to the crop during the growing season. Yield variation can be studied in relation to soil type, weed control, fertilizer application, drainage, soil compaction, and equipment malfunctioning. The information gained can help farmers to take precautions to improve results in subsequent seasons.

Yield and crop quality depend on many factors such as soil fertility, nutrient availability, irrigation, sunlight, and many other inputs. The crop grows in complex response to the variability of these inputs. As an end result, at harvest the yield varies in quality and quantity. Yield in terms of quantity in a grain crop such as corn or wheat is measured by recording the harvested mass and the area, but the quality of the product and may include various physical and chemical aspects depending on the intended purpose. Physical quality of crop includes weight per unit volume, kernel weight, its size, shape, texture and color. Chemical aspects of quality include moisture content, protein content, protein quality and ash content (Government of Alberta, 2003). Quality parameters may also include taste, color, appeal, starchiness and texture when grain is prepared for food. In a root crop such as sugarbeet, yield is measured in terms of tons of sugarbeets per acre. Quality is characterized by the amount of extractable sucrose per unit weight, or

Recoverable Sucrose per Ton (RST). Other beet quality measures include levels of components that limit the sugar extraction process. These include Loss to Molasses (LTM), Harmful Amino Nitrates (HAN), potassium and sodium contents.

1.2 Remote Sensing and Crop Yield

Remote sensing is the science of deriving information about an object from measurements made at a distance from the object, without actually coming in contact with it (Campbell, 2002). The quantity most frequently measured in present day remote sensing systems is the electromagnetic energy reflected from objects of interest. Remote sensing is a potentially important source of data for precision agriculture. In the last three decades remote sensing has emerged as a valuable tool for acquiring information about crop status for crop management. In addition to its many popular applications such as weather mapping and surveillance, remote sensing is now widely used for vegetation mapping, estimating biomass, and quality of vegetation, which leads to a greater understanding of plant functions (Steven et al., 1990).

Remote sensing of crops is being used as a method to augment direct field scouting. Spectrometry, aerial photography, and satellite remote sensing are the three major categories of remote sensing utilized in precision farming. Though these three work on the same basic principle of spectral examination of an object, they differ in magnitude of coverage they provide over an area. Satellite images normally cover large areas, with relatively fixed time interval and large spatial resolutions whereas airborne images cover small areas, with flexible flight schedules and high spatial resolutions.

Nowadays satellite remote sensing systems are utilized to collect information about crops, forests, water bodies and cities. Some of them are dedicated to specific tasks. For example, Radarsat from Canada is aimed at disaster management. The American Landsat systems, Indian IRS systems and the French SPOT are concerned mainly with land observations. The sensors onboard these satellite systems record characteristics of vegetation at the surface as a digital image. Uses for such images include the study of useful timber volume, insect infestation and site quality of forestland (Arvanities, 2002). Other uses include monitoring the growth of crops, or changes in vegetation quality over time.

Considerable efforts have been made to use remote sensing for precision agriculture. Producers may use crop status data and predictive crop growth models to make more precise input and marketing decisions. Producers would be interested in monitoring crop growth to decide crop irrigation, pesticide application and harvest scheduling. Remote sensing images acquired over the growing season allow a producer to monitor crop conditions and compare performance among field sites (Dicker et al., 2001). Crop growth can be monitored with the help of remotely sensed vegetation indexes to predict the probable harvesting date (National Research Council, 1997). Seasonal changes in plant cover and biomass may be linked to prediction of future crop growth, harvesting timings and yield estimates. For example, Paris (National Research Council, 1997) processed data for changes in crop growth for open pollinated cantaloupe to compare the performance of the crop and monitor crop growth. He found that growth graphs (plotting remotely sensed vegetation indexes against various dates over the season) have the potential to better inform growers of the approaching harvesting date. An ability to follow changes in crop development for specific field locations is an emerging area of precision farming.

Researchers have shown that crop yield is significantly related to individual spectral band reflectance and vegetation indices. Bhatti et al. (1991) used Landsat TM images of bare soil to map soil organic carbon content across a large wheat-field to estimate within field variability of soil phosphorous, fertility, and crop yield. Yuzhu (1990) used Normalized Difference Vegetation Index [NDVI = (NIR-Red)/(NIR+Red)] derived from satellite images to predict the wheat yield. Jaggard and Clark (1997) and Clevers (1997) presented research work on yield prediction for sugarbeets, in terms of tonnage, using remotely sensed data. A yield forecasting system was outlined based on their work.

Humburg et al. (2002) used a fertility trial to study correlation between sugar beet quality variables and crop canopy reflectance characteristics. Portable spectroradiometer data and airborne images of trial plots were used to measure sugarbeet canopy reflectance and radiance. The Normalized Difference Vegetation Index (NDVI) and a Green NDVI showed correlation to recoverable sucrose concentration in sugar beet roots.

1.3 Sugarbeet Processing and Harvest Timing

Canopy studies and remote sensing may be useful to the sugarbeet grower as well as sugar processors. Sugarbeet quality, in terms of recoverable sugar per ton (RST) of the processed sugarbeet, has an economic importance in the northern United States (Humburg et al. 2002).

Sugarbeet processing campaigns running from September to March are limited by daily plant capacity and the number of storage days. Processing sugarbeet roots with low recoverable sucrose content is less profitable than processing an equal amount of roots with relatively high recoverable sugar. Cooperatives in the upper Midwest adjust payments to growers according to the recoverable sugar in the crop. Current harvest practices are that an enterprise samples random fields to determine the average recoverable sugar content in sugarbeets. Based on that average recoverable sucrose content, timing of the harvest of a small portion of the total crop is initiated to accumulate sugarbeets amounting to the daily capacity requirement of the plant for early operations.

Study of canopy spectral characteristics using remotely sensed data could help develop relationships between canopy spectral indices, derived from satellite image data, and recoverable sucrose content of sugarbeet roots. If such a relationship existed between sugarbeet quality, in terms of recoverable sucrose content, and vegetation indices, and it could be modeled, farmers could predict their crop quality in terms of recoverable sugar content earlier in the growing season. If the co-operative had available information regarding the relative sugar content of all fields, they could select high sugar content fields for early harvest.

1.4 Objective of This Thesis

Researchers have used all three categories of remote sensing including spectroradiometry, airborne images and imagery from satellite systems in attempts to predict yield and study crop quality. Vegetation indices derived from remotely sensed data gathered at various growth stages have helped to monitor crop development over the growing season. Researchers have attempted to relate vegetation indexes summed or integrated over the season for various crops (Plant et al. 2002). However there has been no attempt to investigate a relationship between canopy spectral indices, derived from satellite image data, and recoverable sucrose content of sugarbeet roots. Research was initiated with the following objectives,

1. Develop a paired data set representing whole-field canopy spectral characteristics from many fields from satellite image data, and whole-field measurements of sugarbeet quality.
2. Test one or more indices of canopy characteristics for a relationship to whole-field average sugarbeet quality
3. Test models utilizing a change in canopy indices over time for relationship to sugarbeet quality.

Chapter 2. Literature review

2.1 Spectral Reflectance

Reflectance is the ratio of the radiant energy reflected by a body to the energy incident on it. Spectral reflectance is the reflectance measured within a specific wavelength interval. A set of reflectance measured over continuous wavelengths constitutes a spectral response pattern commonly known as spectral signature of an object (Campbell, 2002). Physicists and botanist have studied spectral behavior of vegetation canopies and developed mathematical models by estimating the optical properties of leaves and the canopy as a whole. Fig. 1 shows a typical, reflectance-characteristics of vegetation (Campbell, 2002).

Campbell (2002) discusses spectral behavior of living leaf tissue and reflection from canopies. In the visible spectrum of light (400-700 nm) reflectance is controlled by the leaf pigments. In the near infrared region [700-1300 nm] reflectance is controlled by the cell structure. The cuticle, a waxy layer on the surface of leaf, and the upper epidermis are almost transparent to infrared light. They reflect very little infrared radiation. Radiation passing through the upper epidermis then gets scattered by the lower mesophyll tissue and cavity within the leaf. Very little energy is absorbed here and almost sixty percent is reflected back resulting in high NIR reflectance. Reflectance for the light spectrum beyond 1300 nm is controlled by water content in the leaves (Campbell, 2002).

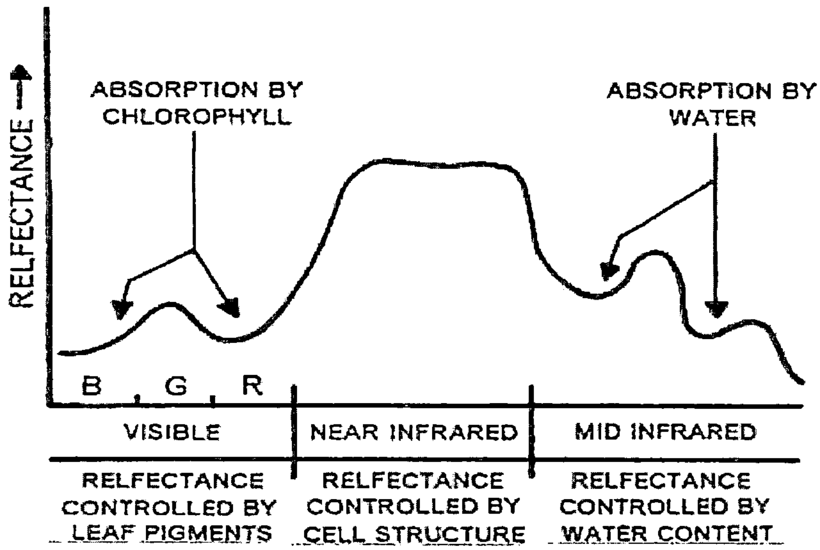

Fig. 2.1 Spectral reflectance of a typical leaf (Campbell, 2002).

2.1.1 Vegetation Indices

Many vegetation indices have been developed for studying spectral characteristics of plants and crop canopy behavior. Some indices that are frequently used in further discussion are defined here.

Leaf Area Index is the ratio of the area of the upper side of the leaves in a canopy projected onto a flat surface to the area of the surface under the canopy (NASA, Glossary).

The Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index, although many vegetation indices have been developed to characterize green vegetation. The NDVI utilizes reflectance of the canopy in the near infrared (NIR) and red (R) bands of the spectrum. This vegetation index is given by

$$NDVI = \frac{NIR - R}{NIR + R}$$

A Soil Adjusted Vegetation Index (SAVI) was introduced by Huete (1988), to minimize soil background effect. It considers reflectance of several bands, and it is given by

$$SAVI = \frac{NIR - R}{NIR + R + L}(1 + L)$$

where, L is a constant related to soil properties providing compensation for soil noise.

A Green NDVI uses the mean reflectance between 565 and 575 nm and an NIR value as the mean reflectance from 865 to 875 nm. Gitelson et al. (1996) found that this index was sensitive to chlorophyll-a concentration. The Green NDVI was calculated as,

$$Green\_NDVI = \frac{(NIR - G)}{(NIR + G)}$$

2.2 Applications of Remote Sensing

Remote sensing for agricultural applications has been used for the last three decades. Some of its wide applications include understanding soil properties, vegetation growth monitoring, vegetation quality assessment, weed detection, nitrogen detection and yield prediction.

2.2.1 Soil Properties

Crop yields do not depend only on varietal differences, fertilizer inputs and irrigation, but also on soil quality. Site-Specific Crop Management frequently involves an understanding of two aspects of soil. The first is sensible classes of soil for the given crop and the second is spatial variability (Burrough et al. 1997). Sudduth and Hummel (1993) studied optical reflectance for measuring soil properties and succeeded in correlating organic matter, cation exchange capacity (CEC) and moisture content to spectra measured with a portable NIR spectrophotometer (Thomasson et al., 2001). Wiegand et al. (1996) used a vegetation index derived from remotely sensed data to map soil salinity over a sugar cane field. Resoma (1981) studied soil moisture content using thermal infrared sensing. Dalal and Henry (1986) and Shonk et al. (1991) attempted to correlate soil properties, in terms of organic matter, with specific spectral responses. Barnes et al. (1996) used Leaf Area Index (LAI) and Soil Adjusted Vegetation Index (SAVI) to understand spectral response in cotton fields for monitoring changes in vegetation patterns and development. Multi-spectral imaging has potential for automated classification of soil mapping. However, bare soil reflectance may be affected by the impact of tillage practices and moisture content (Barnes et al., 1996).

2.2.2 Vegetable and Fruit Quality Assessment

Spectroscopy is potentially used as a tool for Non Destructive Testing of fruits and vegetables. Lu (2001) focused on Hedelfinger and Sam sweet cherries to study diffuse reflectance over the spectral region between 800 nm and 1700 nm and to develop statistical models from the diffuse reflectance data to predict the firmness and sugar content of sweet cherries. He developed statistical models using the partial least squares method to predict the firmness and sugar content of sweet cherries. The models gave relatively good predictions of the firmness of both Hedelfinger and Sam cherries, with correlation coefficient values of 0.80 and 0.65 respectively. Studies by Dull et al. (1989) on cantaloupes indicated a high correlation between NIR reflectance in the range 884 to 913 nm and the soluble solid content. They obtained a high correlation for the slices of cantaloupe tissues used for reflectance measurement.

2.2.3 Weed Detection

Researchers have attempted to distinguish between the crop and weeds using their individual spectral characteristics. Bajwa et al. (2001) used airborne imagery for mapping and modeling spatial infestation density distribution of weeds within soybean fields. Airborne Digital Color Infrared (CIR) sensors were used instead of ground-based sensors or vehicle mounted sensors to acquire very high-resolution images. The study was carried out using three broad bands of G (500-600 nm), R (600-710 nm) and NIR (710-810 nm). The study also supported the findings of Menges et al. (1985) that color infrared photography could be used to distinguish weed reflectance from crop reflectance. Goel et al. (2002) acquired airborne images over cornfields to find that bands centered at 675.98 and 685.17 nm in the red region, and from 743.93 to 830.43 nm in the near infrared region had the best potential for detecting weeds in corn. They used LAI to distinguish corn and weeds. Another approach to detect weeds in a sugar beet crop was developed by Terawaki et al. (2002). They used images acquired by a digital camera (Fine Pix, Fuji Film, Inc) to develop an algorithm, necessary for an automatic thinner and a weeding machine. This algorithm used discriminant functions developed from shape characteristics such as area of leaf, ratio of area and perimeters for sugarbeet, green amaranth, wild buckwheat and field horsetail.

2.2.4 Growth Characteristics

Often, crop yield in a field varies when inputs such as fertilizers, pesticides and herbicides are applied uniformly across the field. Combined use of visual interpretation of computer enhanced remotely sensed imagery and physical assessment of crop areas has proven useful to improve understanding of crop growth in fields. It is understood that the reflectance governed by chlorophyll will vary as the plant grows. Chen et al. (2002) studied Pak-choi Chinese cabbage using multi-spectral imagery. That analysis of chlorophyll content and leaf moisture content distributions showed potential applications in monitoring the growth of vegetables. They developed a sensing algorithm based on plant physiological status and evaluated effective absorption wavelength bands for chlorophyll and moisture content.

High-spatial resolution multi-spectral imagery was used by Johnson et al. (2001) to delineate low, moderate and high vigor zones within a Vineyard. They used the NDVI, derived for each pixel, to emphasize differences in the amount of leaf area per unit ground area. After the analysis Johnson et al. found that the canopy reflectance was greatest in the low-vigor zone and lower in the high vigor zone. The results of this work allowed harvesting vines by vigor zones, and were found useful in maintaining the uniformity and quality of wine blending from zone to zone.

Development of crop monitoring methods from remotely sensed vegetation indices has the potential to inform growers of approaching harvest date. Paris (National Research Council, 1997) suggested a methodology to characterize crop growth by calculating relative differences in the vegetation index at any one time, or over the growing season. Yao et al. (2002) concentrated on identifying the correct wavelength ranges from hyper-spectral imagery to extract information on various growth indicator parameters, such as corn nitrogen content, population, yield, and grain quality. They found that for a late season image the most useful bands were centered at the green region

(~ 550 nm) and the NIR region. The spectral reflectance measured in this region was used to model relationships between the reflectance and corn yield. They obtained a high correlation ($R^2 = 0.75$) in the later season for the NIR band. For, reflectance and population, they used NIR, and obtained a correlation of 0.70. For the model relating NIR and green reflectance to nitrogen, the range of correlation was from -0.86 to 0.75 for different dates in the season. They also found that for yield estimation NIR was the best wavelength band, whereas the best wavelengths to measure nitrogen content were centered at the green and red bands.

2.2.5 Nitrogen Detection and Characterization

Nitrogen and chlorophyll content in crop leaves has been of interest to researchers worldwide, as nitrogen stress is frequently associated with leaf chlorophyll content, which can be characterized by spectral reflectance measurements. Reid et al. (2002) developed a vision-based reflectance sensor at the John Deere Technology Center. This sensor promises a possible solution to precise assessment of nitrogen and chlorophyll in crop leaves by eliminating the background effects using image processing, and detecting only crop canopy response in specific image wavelengths. Kim (2000) proposed N estimation based on the theory that spectral reflectance is inversely correlated to the N content of the crop canopies. Aerial photographs, both color (RGB) and color infrared (CIR) were used to predict nitrogen uptake and yield by Blackmer et al. (1995). They used film cameras to capture the image and then scanned the image into the computer for further processing and analysis. The green and red components of color displayed in an aerial photograph were highly correlated with grain yield. They put specific filters over the camera lens to make it possible to generate a black-and-white photograph with gray-tones that were indicative of crop greenness and identified the areas within a field that were likely to be N deficient. They found that a ratio of reflectance in the red band and the near infrared band was also highly correlated with crop N status (Blackmer et al, 1995).

Lee et al. (2000) developed a nitrogen sensor to assess nitrogen in corn and apply fertilizers precisely. They constructed an in-field hyperspectral sensor system. The research was based on the findings that nitrogen content in plant leaves affects the spectral reflectance. They measured the reflected light energy from corn leaves for different ranges of wavelengths. Their analysis of leaf spectra indicated that higher leaf nitrogen content resulted in lower reflectance near 550 nm. Thomas and Gausman (1977) indicated that canopy reflectance near 550 nm showed good separation of leaf nitrogen concentration, and could be used to detect N deficiency of crop plants.

Nitrogen management is critical to root crops such as sugarbeet. Campbell and Kern (1983) studied the relationship between sugarbeet quality and other yield components, and found that management of nitrogen fertilizer is important in determining beet quality. Amino-nitrogen concentration has a large influence on recoverable sucrose per ton and also indicated that improper management of the nitrogen in the system has negative effects on quality and yield.

Moraghan (1998) categorized sugarbeet fields by observing color aerial photographs and classifying them into 'green', 'yellow-green' and 'yellow' areas. The green canopies were found to have an abundance of nitrogen in leaves, whereas the yellow areas contained lower levels of nitrogen.

2.2.6 Yield Prediction

Remotely sensed data provide information about crop characteristics. It has been used as an estimator of various vegetation parameters, such as leaf area index (LAI) and biomass. Baret and Guyot (1991) discussed the potential and suitability of vegetation indexes. Different vegetation indexes such as the NDVI and Ratio Vegetation Index (RVI=NIR/red) derived from information contained in spectral bands are well correlated with canopy characteristics such as LAI, percent ground cover, and productivity (Baret and Guyot, 1991).

Knowledge of crop growth and its estimation in an early stage is important from the commercial and management aspects for the grower and processor. There are many methods and models developed for yield estimation. Remote sensing can provide information on the actual status of agriculture crops. Zhao (2002) discussed the performance of such models when they were extended from field to regional scales. He found that most models developed at the field scale do not perform satisfactorily. The models generated for fields, are limited to only small areas, and do not account for the chances of large spatial variation of input parameters on a regional scale.

Lobell and Arner (2001) used Landsat 7 satellite imagery to predict regional wheat production. They estimated wheat yields and planting date using a field-based model of crop production, combined with multi-date Landsat imagery in Mexico. They found that the difference between the estimated and reported wheat production to their surprise was only 0.8 percent in 2 years. Liu and Zheng (1990) discussed a project conducted in China for estimating production of winter wheat by using remote sensing information combined with a ground network. Crop reflectance data were collected by Landsat TM scanner. They estimated crop yield with prediction errors less than 5% for 3 years. Benedetti and Rossini (1993) also developed a linear regression model for wheat yield estimates and prediction, based on NDVI integration over the wheat grain filling period.

Remote sensing and its associated technologies have been used also in paddy yield estimation. Muthy et al. (1994) attempted to correlate NDVI and paddy yield. They found that NDVI varied for different phenological stages of the crop. The model developed predicted the yield with deviation varying from 0.82 to 9.75 % in 9 plots covering 7031 ha. of land, under the crop. Mohamad et al. (1994) found a correlation between paddy yield and vegetation indexes. The coefficient of correlation for the NDVI, Ratio Vegetation Index- RVI (band4/band3) and RVI (band5/band3) were 0.85, 0.55 and 0.32 respectively. The results were consistent with similar attempts by other researchers, which suggested that the NDVI had better correlation with paddy yield. They compared yield estimation obtained from field data and yield estimation obtained from satellite data and found an error of about 30 %. They proposed an equation for yield estimation from satellite data as,

Yield (kg/ha) = 34.30 x ($NDVI_{sat}$ – 0.1836) – 237.85.

They postulated that the errors in the estimations were due to differences in the paddy phenology cycle at the time the satellite data were acquired, and the time the field measurements were taken. Rajapakse et al. (2000) attempted modeling of Tea yield using the data obtained from the IRS-1C satellite and concluded that logarithmic functions yielded the strongest relationship between LAI and NDVI.

Researchers also have studied root crops such as sugarbeet for yield prediction using remotely sensed data. Bauman (1994) linked physical remote sensing models with crop growth simulation models applied for sugarbeet. Jaggard and Clark (1990) proposed a productivity forecasting system based on a model of sugarbeet crop growth, and spectral measurements obtained using a spectrometer over the crop canopy. They proposed a model to predict the productivity of sugarbeet as,

$$w = e\int fR_s dt$$

The term w is a productivity of sugarbeet. The constant e in the model is the net coefficient of conversion of solar energy into plant material, while f is the fraction of solar irradiance, R_s, intercepted by the crop. The fraction f, at any time is estimated from a near-infrared/red reflectance ratio. The model developed was based on the spectral measurements in two bands, 600-660 nm and 780-940 nm. Jaggard and Clark (1990) found that this model held better for the results of yield prediction over a national scale than on individual fields.

Clevers (1997) developed an approach for sugarbeet yield prediction based on optical remote sensing data. He used a weighted difference vegetation index (WDVI). He defined WDVI as a weighted difference between measured NIR and red bands, assuming the ratio of NIR and red reflectance of a bare soil was constant. The relation proposed was,

$$WDVI=NIR-(C*Red)$$

Where, NIR= total measured NIR reflectance, Red= total measured red reflectance, and *C*= Ratio between NIR and red reflectance of soil.

This WDVI was used for estimating LAI to the inverse of an exponential function,

$$LAI = -\frac{1}{a}\ln(1-\frac{WDVI}{WVDI_{\infty}})$$

Here *a,* is the parameter describing the rate at which the LAI value reaches its asymptotic value $WDVI_{\infty}$. The LAI value is used to find out the fraction of absorbed photosynthetically active radiation (FPAR). Clevers proposed a very simple model, which linearly relates yield with FPAR as,

$$Yield = c + d.FPAR(t)$$

Where, *c* and *d* are empirical parameters. Closeness of the estimated yield value and the actual yield values suggests thorough testing of this approach for its general applicability to other agriculture crops, though he proposed the model for sugarbeet yield.

Xie (1997), studied spectral characteristics of sugarbeet leaves and linked the to sugar content of sugarbeet roots and other beet quality variables. He used a spectroradiometer for recording the spectral reflectance and aerial images with spatial resolution of 1m for his research. Xie correlated a number of sugarbeet quality measures such as sodium content, harmful amino nitrates (HAN), loss to molasses (LTM) and recoverable sugar per ton (RST) to spectral response. However the analysis gave highest correlation for sucrose content (0.48), sodium (0.76) and sucrose per ton (0.36). Though a weak correlation between spectral properties of canopy and sugar quality was established, the statistically significant relationship between spectral characteristics and sugar content in sugarbeets suggests the study of ways to model sugarbeet quality with spectral measurement of canopy.

Humburg et al. (2002) used a fertility trial to correlate sugarbeet quality variables to canopy spectral characteristics. They used a portable spectroradiometer, and airborne images of the trial plots to measure canopy reflectance and radiance. A Green NDVI and the NDVI chosen to represent the canopy characteristics showed correlations with the recoverable sucrose concentration. The spectral indexes were derived from the green (570 nm), red (660 nm) and NIR (870 nm) wavelengths. They suggested the use of multispectral images for the mapping of variability in crop quality. Both a conventional NDVI and the green NDVI, indices showed correlation to recoverable sucrose concentration in sugarbeet roots for the spectrograph data and the airborne image data.

As discussed above, various studies have attempted to correlate the quality of sugarbeet with canopy reflectance data collected with spectroradiometers and airborne imagery. However, there has been no attempt to model a relationship between canopy spectral indices derived from satellite image data and quality of sugarbeet roots. Accordingly, an investigation was conducted to determine suitability of the NDVI, a Green NDVI and the SAVI derived from remotely sensed satellite data, as possible predictors of recoverable sucrose content in sugarbeets.

Chapter 3. Materials and Methods

Sugarbeet quality data and satellite spectral data were collected to investigate the relationship between them. An approach was developed to model quality with various vegetation indices. The literature review suggested potential and limitations of various vegetation indices selected or developed by researchers.

3.1 Spectral Indices Utilized

The Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index, although many vegetation indices have been developed to characterize green vegetation. The NDVI utilizes reflectance of the canopy in the near infrared (NIR) and red (R) bands of the spectrum and is given by,

$$NDVI = \frac{(NIR - R)}{(NIR + R)}.$$

A Soil Adjusted Vegetation Index (SAVI) was first introduced by Huete (1988) to minimize soil background effects. It is given by,

$$NIR = \frac{NIR - R}{NIR + R + L}(1 + L)$$

Where, L is a constant related to soil properties providing compensation for soil noise. Its value is 0.5 for a normal vegetation density.

A Green NDVI uses the mean reflectance between 565 and 575 nm and an NIR value as the mean reflectance from 865 to 875 nm. Gitelson et al. (1996) found that this index was more sensitive to chlorophyll-a concentration. The Green NDVI was calculated as, $Green\_NDVI = \frac{(NIR - G)}{(NIR + G)}$.

3.2 Database Used

Two databases were used to test for large-scale correlation of quality and canopy characteristics. The sugarbeet growing region of the Southern Minnesota Beet Sugar Co-operative in Renville, Minnesota was the source of field data and images.

3.2.1 Satellite Imagery and related database

Multi-spectral satellite images were obtained during the 2002 growing season. Image date included July 30, August 27 and September 16. Images were acquired from the SPOT satellite platform[1]. These images were obtained from RESOURCE 21, a commercial source of digital data. The images have a 20-meter, 8-bit resolution. Band B1 spanned wavelengths from 500 to 590 nm (green). Band B2 covered the spectrum from 610 to 680 nm (red). Band B3 spanned 790 to 890 nm (NIR). B4 measures from 1580 to 1750 nm.

Each image was projected into the Universal Transverse Mercator (UTM), World Geodetic Survey 1984 (WGS-84), Zone 15 coordinate system. The first image was georegistered using recorded coordinates for a set of ground control points in ERDAS IMAGINE 8.5 (ERDAS, Inc., 2001). The other two images were registered through image-to-image registration. Each sugarbeet field in the image was identified and an Area of Interest (AOI) was developed to isolate pixels representing that field. Digital numbers representing canopy reflectance band measurements were extracted from the areas of interest.

1. Images for this work were provided by, Resource21 under cooperation with a USDA grant (MSU- Subcontract: GC031-02-Z2485). The support of Resource21 is gratefully acknowledged.

3.2.2 Sugarbeet Field Database

Sugarbeet quality data were extracted from the year 2002 Field Database of the Southern Minnesota Beet Sugar Co-operative SMBSC), Renville, Minnesota. The database was in the form of a .dbf file as a part of an ArcView shape file, and included geographic data as well as field attribute data. Geographic data included field boundaries. Attribute data included sugarbeet variety grown in each field, field average sucrose percentage, and average sugarbeet yield (tons/acre).

Quality of sugarbeets had been determined by the cooperative from samples taken from trucks as harvested beets were delivered to piling sites. Approximately 30 % of the truckloads were sampled. Samples, containing approximately 10 roots were bagged and delivered to the Tare laboratory at the Southern Minnesota Beet Sugar Cooperative (SMBSC) in Renville, Minnesota. Samples were processed there to determine the percentage of sucrose, and the concentration of nitrates in the roots. From there a value of recoverable sucrose per ton of sugarbeet roots was calculated. Recoverable sucrose per ton is the primary method of quantifying sugarbeet quality in this region. The SMBSC database gives pounds of sucrose per acre. This was determined by multiplying average yield, in tons per acre, by the recoverable sucrose per ton calculated from samples of that field. For purposes of this work, the value of recoverable sucrose per ton was back-calculated as recoverable sucrose per acre divided by tons per acre.

3.2.3 Sugarbeets varieties in database and Rhizomania in Sugarbeets

A number of distinct varieties of sugarbeet were represented in the study area. Rhizomania, or Beet Necrotic Yellow Vein Virus (BNYVV) is a soilborne disease common through the SMBSC growing area. The disease causes yellowing of the beet leaves and reduces both yield and recoverable sucrose. Sugarbeet varieties are classified as resistant to the disease or conventional varieties. Some fields were planted to mixed varieties of resistant strains, and these fields represent one of the classes of fields (Mixed Rhizomania) tested for correlation of quality and canopy spectra. Other fields were planted to mixed strains of conventional varieties and this class (Mixed Conventional) was also tested. Other classes tested represented fields planted to a pure strain of a specific hybrid. These included ACH999, B3945, B4811, and B4930. B3945 is a conventional variety whereas B4811 is considered as a rhizomania tolerant variety. These two varieties had a sufficient number of fields to warrant testing. Table 3.1 shows a sample database extracted from the cooperative's database.

Table 3.1 Sample Database Extracted From Master Database of the Southern Minnesota Beet Sugar Cooperative, Renville, MN.

CONT_FIELD*	VARIETY	CNITRATES**	YTONS_A***	Y_SUGAR+	YSGR_A#
33203_1	ACH999	25	21.76	17.25	6960
182100_1	B4811	26	23.06	16.4	6948
33203_4	Mixed conventional	26	21.38	17.31	6865
835100_3	B3945	27	21.73	16.18	6442
346505_3	B4811	28	22.94	16.92	7171
68300_5	ACH999	28	23.2	17.49	7540
256000_5	B3945	29	22.68	15.75	6508
33203_3	ACH999	30	20.92	17.95	7009
33203_5	B3945	30	49.02	18.05	16527
346505_1	B4811	30	23.26	16.85	7239
675105_1	Mixed conventional	31	22.7	16.98	7128
264000_1	Mixed conventional	32	25.18	17.37	8120
306900_1	Mixed rhizo	32	16	15.03	4336

*CONT_FIELD = Field Identification Number
+Y_SUGAR = % of Recoverable Sugar
#YSGR_A = Sugar recovered in pounds per acre
***YTONS_A = Sugarbeet yield in tons per acre
Variety = Class or of Variety
**CNITRATES = Nitrate Concentration

3.2.4 Image overlap

The areas subtended by the individual satellite images acquired on these dates did not completely coincide. Each image captured approximately 275 sugarbeet fields within the cooperative's database. It was necessary to identify sugarbeet fields common to all three images. Fig. 3.1 shows the locations of fields growing variety B3945 of sugarbeets. These fields appeared in all three images taken on July 30, August 27 and September 16 for the year 2002. They appear in the figure as light blue highlighted areas.

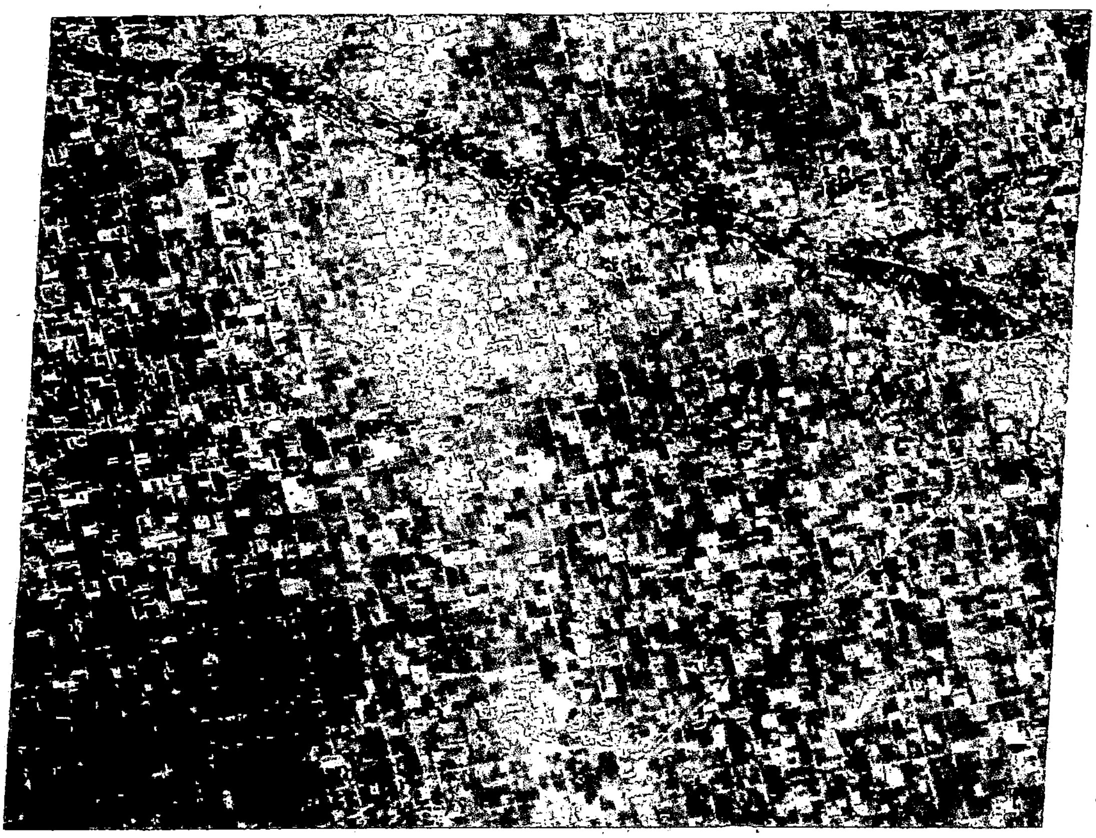

Fig. 3.1 SPOT image in September 16, 2002 highlighted with sugarbeet fields, common also visible in images taken on July 30, 2002 and August 28, 2002

3.2.5 Procedure to extract DN numbers

The following is the procedure used to generate a database containing DN numbers for areas of interest for each field.

1. Boundaries of each field from the quality database were identified and superimposed on each image with the help of ERDAS IMAGINE 8.5, image-processing software.
2. Areas of interest were established for each field common to the 3 images.
3. The pixels for each AOI layer were extracted using the ERDAS IMAGINE, utility command, "Convert Pixels to ASCII".
4. The pixels extracted were saved in ASCII format. They were subsequently imported into an MS-EXCEL spreadsheet. A sample data set for an AOI extracted as DN numbers is given in Table 3.2.

Table 3.2 Sample data extracted from image

X	Y	B1	B2	B3	B4
321990	4957059	178	139	124	190
322014	4957059	184	152	128	180
322038	4957059	188	166	118	181
322062	4957059	151	115	137	159
322086	4957059	174	141	118	178
322110	4957059	186	154	116	184
322134	4957059	150	112	143	159
322158	4957059	156	120	135	172
322182	4957059	166	133	127	182
322206	4957059	184	154	119	194
322230	4957059	154	114	149	160

Where,
X = X Coordinate and Y= Y Coordinate
B1 = Band B1 covering wavelengths from 0.50 to 0.59 μm (green)
B2 = Band B2 covering wavelengths from 0.61 to 0.68 μm (red)
B3 = Band B3 covering wavelengths from, 0.79 to 0.89 μm (NIR), and
B4 = Band B4 covering wavelengths from 1.58 to 1.75 μm.

3.3 Radiometric Correction of Satellite Images

Remote sensing images came in the form of digital numbers (*DN*) or scalar values. These values depend on a host of factors such as the ambient illumination conditions, system characteristics, and these values are generally affected by different sources of noise. The prominent sources of variability are the variable sun light intensity, sun angle, sensor-induced noise and, atmospheric scatter (Campbell, 2002). In the present study considerations were given to changes in canopy spectral reflectances between dates in addition to canopy characteristics on individual days. Therefore, the first task to perform on the image after geometric corrections was to rectify the image values for variable illumination and atmospheric conditions. The correction for the atmospheric effects was important to allow comparison of canopy characteristics acquired under different atmospheric conditions. All raw *DN* numbers for the areas of interest required radiometric correction prior to meaningful comparison over time.

Researchers have used many approaches to correct the image radiometrically. Moran et al (2001) used one method of radiometric correction to measure atmospheric conditions during the overpass with specialized on-site sensors and then used an atmospheric radiative transfer model (RTM) to convert the aircraft radiance measurements to surface reflectance factors. A radiative transfer model simulates radiation transfer processes in certain media, such as vegetation and atmosphere. For vegetation, it computes the interaction between solar radiation and plants. Solar radiation reflected from the Earth's surfaces, and measured by satellites, depends strongly on the angle of the sun and the satellite in relation to the surface. The limitation of this method is that it requires the aircraft sensor to be calibrated to convert *DN* to radiance before atmospheric corrections are applied (Moran et al., 2001).

Another common approach of calibrating the image is to convert the *DN* into apparent reflectance. This is the ratio of reflected spectral radiation incident on the airborne sensor and the incident spectral radiation measured on the surface or onboard the aircraft. This method is implemented by a set of sensors of which one is the airborne sensor that looks down on the target surface, while another onboard sensor looks upward for the incident radiation. The second sensor could also be mounted in the field. In both the cases, the ratio of downward-looking and upward-looking sensor values will give the apparent reflectance (Bajwa et al., 2002).

A third method of calibrating the image is to convert un-calibrated image bands into normalized bands or band ratios used as vegetative indices. These indices compensate for the errors that are common in all channels of a multispectral image. This approach minimizes errors due to the sensor, the variable illumination, and the atmospheric effects. (Bajwa et al., 2002)

Moran et al. (2001) developed a refined approach of calibrating Landsat 5 and Landsat 7 images to derive a linear regression equation between the *DN* and relative reflectance based on objects of known reflectance within the field of view of an airborne camera. The objects may be dark objects such as a water body not prone to algae growth or light objects such as painted plywood or a white tarp with a known reflectance, which can be identified in the field.

The research described here used the empirical line method (ELM), (Moran et al., 2001), as the first two methods require more than one sensor, pre-calibration of sensors, or targets large enough to be identified in the image. The third method only minimizes the errors due to the sensor, the variable illumination, and the atmospheric effects. Digital numbers were corrected using an empirical line approach, where simultaneous field spectral measurements were made at three spatially uniform ground targets, called Pseudo Invariant Objects (PIO). Reflectance data of the pseudo invariant objects (which are considered to have a constant reflectance over time were collected with a portable battery powered, Spectroradiometer, Model No. MSR16R manufactured by CROPSCAN, Inc. Rochester, MN, USA. This instrument measures percent reflectance by collecting both incident and reflected radiation. Data are collected for 16 bands centered at 460, 510, 560, 568, 610, 660, 661, 710, 760, 810, 830, 905, 1050, 1160, 1260, and 1650 nanometers. The CROSPSCAN radiometer was held at a height of 2 meters for the data reflectance measurements. The three objects used were a large lime pile, asphalt coated airport runway strip and a small water body (Water accumulated in a gravel pit). Sample reflectance values for each object are given in table 3.2, 3.3 and 3.4. Linear regression models were derived to relate the reflectance measured at the ground with the radiance measured by the remote sensor.

The *DN* numbers were extracted for each band in the images for bright (Lime pile in the sugar factory yard), moderately reflective, (Asphalt-apron), and dark, (Waterbody-water accumulated in a gravel pit), objects. Reflectances were also measured for these targets using the CROPSCAN instrument. Linear regression equations were developed between the reflectances measured by satellite sensors and reflectances measured by the spectroradiometer. The DN recorded for each wavelength band was then transformed into the apparent reflectance using the linear regression equation. The adjusted pixel values were used to minimize illumination and atmospheric effects between images. The image data after calibration represented the apparent reflectance of the sugarbeet field and was suitable for use in models of canopy and quality. Table 3.6 gives statistics for the empirical line method calibration, in this application. The linear equation to convert digital number (*DN*) to reflectance is given.

Table 3.3 CROPSCAN-Reflectance for waterbody (Gravel Pit)

Wavelength, 560 micrometer	*Wavelength, 660 micrometer*	*Wavelength, 830 micrometer*
15.35	9.9	2.43
15.38	10.02	2.67
15.51	10.12	2.39
15.53	10.16	2.28

Table 3.4 CROPSCAN-Reflectance for Lime Pile

Wavelength, 560 micrometer	*Wavelength, 660 micrometer*	*Wavelength, 830 micrometer*
62.15	64.65	72.8
58.29	60.93	69.81
63.07	65.49	73.93
62.74	65.31	71.69

Table 3.5 CROPSCAN-Reflectance for Asphalt (Airport Apron)

Wavelength, 560 micrometer	*Wavelength, 660 micrometer*	*Wavelength, 830 micrometer*
59.33	59.09	58.05
59.46	59.17	58.1
59.12	58.75	57.7
58.98	58.55	57.27

Table 3.6. Empirical Line Method Calibration; Target Spectral Reflectance values after calibration

Date	Description	Green	Red	NIR
7/30/02	Lime pile (y image)	227.75	212.1	169.95
	Lime pile (x cropscan)	43.10	48.89	59.46
	Target Reflectance After Calibration	2.76	2.66	1.62
	Asphalt (y image)	215.05	211.7894737	87.94
	Asphalt (x cropscan)	12.94	14.99	17.02
	Target Reflectance After Calibration	2.47	2.66	0.50
	Water (y image)	138.55	85.66	24.44
	Water (x cropscan)	16.52	11.67	3.04
	Target Reflectance After Calibration	0.76	0.66	-0.37
	Regression Equation	(DNg-104.59)/44.59	(DNr-43.41)/63.21	(DNnir+51.39)/72.75
8.27/02	Lime pile (y image)	146.75	190.75	139.95
	Lime pile (x cropscan)	43.10	48.89	59.46
	Target Reflectance After Calibration	4.18	3.91	3.09
	Asphalt (y image)	79.48	81.96	62.32
	Asphalt (x cropscan)	12.94	14.99	17.02
	Target Reflectance After Calibration	1.20	1.639	1.50
	Water (y image)	50.66	31.88	15.44
	Water (x cropscan)	16.52	11.67	3.04
	Target Reflectance After Calibration	-0.07	0.59	0.53
	Regression Equation	(DNg-52.34)/22.55	(DNr-3.50)/47.85	(DNnir+10.80)/48.738
9/16/02	Lime pile (y image)	123.35	150.45	141.1
	Lime pile (x cropscan)	43.10	48.89	59.46
	Target Reflectance After Calibration	2.64	2.61	3.10
	Asphalt (y image)	90.72	92.40	75.27
	Asphalt (x cropscan)	12.94	14.99	17.02
	Target Reflectance After Calibration	1.96	1.88	2.04
	Water (y image)	78.25	54.75	43.62
	Water (x cropscan)	16.52	11.67	3.04
	Target Reflectance After Calibration	1.70	1.41	1.53
	Regression Equation	(DNg+3.78)/48.04	(DNr+57.32)/79.43	(DNnir+51.93)/62.25

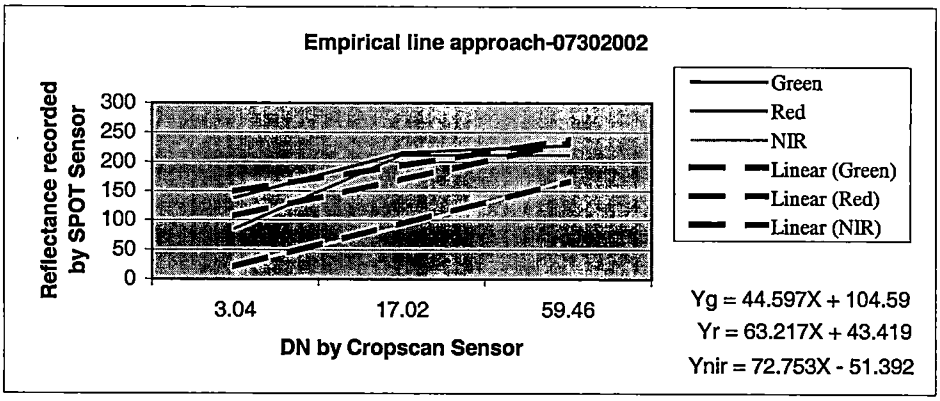

Figure 3.2.1 SPOT DNs vs. Cropscan reflectance values (July 30, 2002)

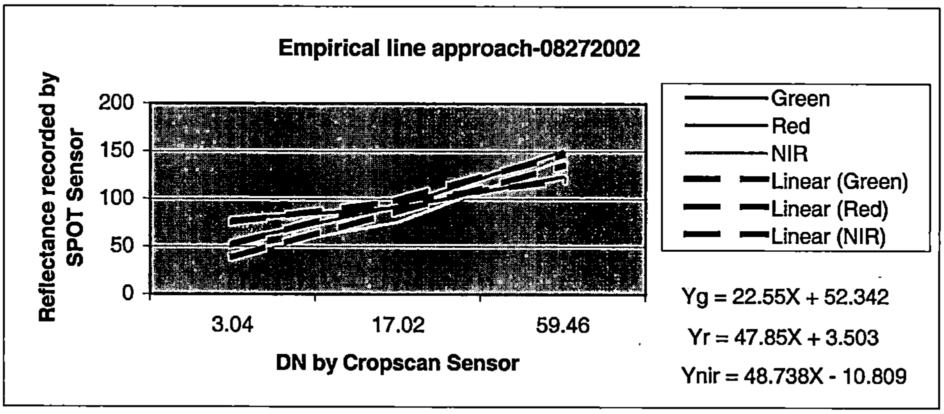

Figure 3.2.2 SPOT DNs vs. Cropscan reflectance values (August 27, 2002)

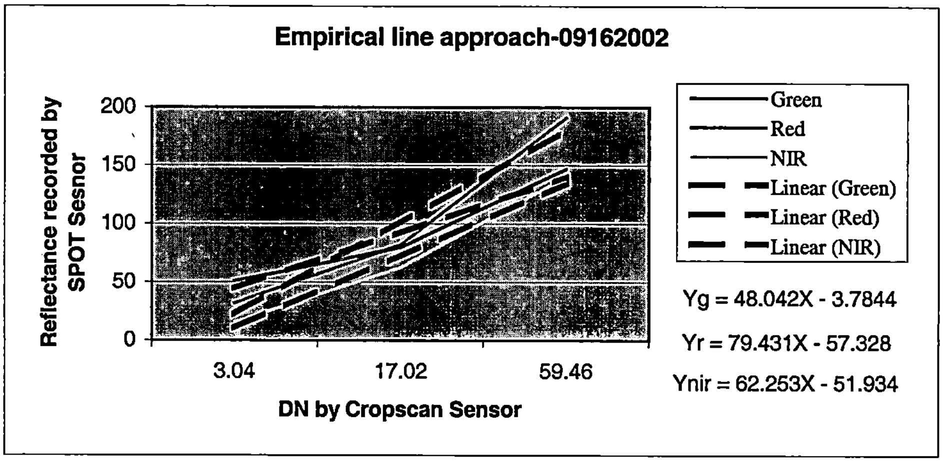

Figure 3.2.3 SPOT DNs vs. Cropscan reflectance values (September 16, 2002)

3.5 Arriving at Spectral Indices

Radiometrically corrected canopy reflectance spectral data obtained from SPOT images were used to derive vegetation indexes for the pixels representing a field. Digital Numbers for each of the four bands were radiometrically corrected. Vegetation indices were calculated on a pixel-by-pixel basis. These vegetation indices were averaged for the pixels representing each field and were used to link recoverable sucrose content per ton of sugarbeets.

3.6 Statistical Analysis: Linear and Multiple Regression Analysis

Relationships between spectral reflectance of sugarbeet leaves and recoverable sugar content in roots were modeled after processing the image data and pairing it with field quality data.

The relationship between a qualitative dependent variable Y, recoverable sucrose per ton of sugarbeet, and other independent variables such as Green NDVI, NDVI and SAVI was tested. Four classes of sugarbeet varieties were analyzed. These consisted of Mixed Conventional and Mixed Rhizomania, and two pure strains, B3945 and B4811. B3945 is a widely used conventional variety while B4811 is a widely planted, rhizomania tolerant variety.

The vegetation indices were calculated for individual dates. The difference between each vegetation index for two consecutive image dates was also calculated as a representative measure of the change in canopy characteristics between image periods. Linear Regression Analysis was carried out to model the relationships (Table 3.7 and 3.8).

Table 3.7 Variables tested as independent variables against recoverable sucrose per ton of sugarbeets (For sugarbeet growing season 2002). All models are simple linear regressions.

July 30	August 27	September 16	August-July	September-August	September-July
NDVI[a]	NDVI[a]	NDVI[a]	Change in NDVI[d]	Change in NDVI[d]	Change in NDVI[d]
GNDVI[b]	GNDVI[b]	GNDVI[b]	Change in GNDVI[e]	Change in GNDVI[e]	Change in GNDVI[e]
SAVI[c]	SAVI[c]	SAVI[c]	Change in SAVI[f]	Change in SAVI[f]	Change in SAVI[f]

a. Recoverable sucrose content and NDVI on July 30, August 27, September 16, 2002
b. Recoverable sucrose content and Green NDVI on July 30, August 27, September 16, 2002
c. Recoverable sucrose content and Saves on July 30, August 27, September 16, 2002
d. Recoverable sucrose content and changes in NDVI from July 30 through August 27, 2002, August 27 through September 16, 2002 and July 30 through September 16, 2002.
e. Recoverable sucrose content and changes in Green NDVI from July 30 through August 27, 2002, August 27 through September 16, 2002 and July 30 through September 16, 2002.
f. Recoverable sucrose content and changes in SAVI from July 30 through August 27, 2002, August 27 through September 16, 2002 and July 30 through September 16, 2002.

Table 3.8 Variables tested in Multiple Linear Regression models for correlation to recoverable sucrose per ton of sugarbeets (For sugarbeet growing season 2002).

NDVI[g] Model	GNDVI[h] Model	SAVI[i] Model	NDVI, GNDVI, SAVI Model[j]	All Index Model[k]
ΔNDVI August-July + ΔNDVI Sept.-August	ΔGNDVI August-July + ΔGNDVI Sept.-August	ΔSAVI August-July + ΔSAVI Sept.-August	ΔNDVI Sept.- July + ΔGNDVI Sept.-July + ΔSAVI Sept.-July	(ΔNDVI, ΔGNDVI, ΔSAVI) August-July + (ΔNDVI, ΔGNDVI, ΔSAVI) Sept.-August

g. Recoverable sucrose content and interaction of changes in NDVI from July to August and August through September.
h. Recoverable sucrose content and interaction of changes in Green NDVI from July to August and August to September.
i. Recoverable sucrose content and interaction of changes in Saves from July to August and August to September.
j. Recoverable sucrose content and interaction of changes in NDVI from July to September GNDVI from July to September, and SAVI from July to September.
k. Recoverable sucrose content and interaction of changes in NDVI, GNDVI, and SAVI from July to August, and from August to September.

Chapter 4: Results and Discussion

Data for four classes of sugarbeet fields grown within the area of operation of the Southern Minnesota Beet Sugar Co-operative were analyzed. The number of sugarbeet fields common to all three images varied. Variety B4811 was grown in 41 fields. Mixed conventional varieties were grown in 24 fields. The variety B3945 was used in 24 fields, and 10 fields were planted to a mixture of Rhizomania tolerant varieties. Field average recoverable sucrose ranged from 240 to a high of 322 pounds per ton of sugarbeet. Mean NDVI ranged from 0.39 to 0.52. The GNDVI and SAVI ranged from 0.34 to 0.59 and 0.46 to 0.69 respectively.

Mean values of vegetation indices on individual dates for each variety class of sugarbeets calculated on field-by-field basis are given in Table 4.1. Mean values of change in vegetation indices over two dates in the season are given in Table 4.2. These were calculated on a field-by-field basis.

4.1 Sugarbeet Quality and Canopy Spectra Correlations.

An analysis was performed for each variety separately to investigate possible statistical links between recoverable sucrose per ton and differences in canopy indices tested for each individual date.

The correlation coefficient (R^2) for models between spectral indices and sucrose content varied widely for each variety. Table 4.3 gives the values of correlation coefficients and probabilities for each variety class. The results of the analysis suggested little correlation, if any, for all the classes of sugarbeets.

Analyses were conducted to correlate the change in canopy indices between two image dates to sugarbeet harvest quality. Tables 4.1 and 4.2 contain average vegetation indices and change in vegetation indices respectively. Tables 4.3, 4.4 give correlation coefficients for linear regression models relating vegetation indices and quality data for each variety class.

Table 4.1 Mean values of Vegetation Indices on Individual Dates for classes of field varieties studied.

Sugarbeet Class	NDVI (July)	NDVI (August)	NDVI (Sept.)	GNDVI (July)	GNDVI (August)	GNDVI (Sept.)	SAVI (July)	SAVI (August)	SAVI (Sept.)
Mix. Rhizo.	0.39	0.50	0.40	0.34	0.58	0.38	0.52	0.67	0.53
Mix.Conv.	0.42	0.52	0.39	0.36	0.59	0.38	0.57	0.69	0.53
B3945	0.40	0.48	0.37	0.38	0.58	0.34	0.53	0.64	0.50
B4811	0.40	0.49	0.39	0.34	0.57	0.37	0.46	0.76	0.51

Table 4.2 Mean values of Changes in Vegetation Indices over the Season for classes of field varieties studied.

Sugarbeet Class	NDVI (07-08)	NDVI (08-09)	NDVI (07-09)	GNDVI (07-08)	GNDVI (08-09)	GNDVI (07-09)	SAVI (07-08)	SAVI (08-09)	SAVI (07-09)
Mix. Rhizo.	0.11	-0.10	0.01	0.24	-0.20	0.04	0.15	-0.13	<0.01
Mix.Conv.	0.09	-0.13	0.04	0.22	-0.21	-0.01	0.12	-0.16	-0.03
B3945	0.08	-0.11	-0.03	0.20	-0.21	-0.01	0.10	-0.14	-0.03
B4811	0.09	-0.10	-0.01	0.22	-0.19	0.03	0.30	-0.25	0.05

Table 4.3 R^2 values for correlation of recoverable sucrose content with different spectral indexes.

Variety	Date	NDVI		Green NDVI		SAVI	
		R^2	Pr.	R^2	Pr.	R^2	Pr.
Mixed Rhizo. (10 Fields)	July 30, 2002	0.487	0.025	0.087	0.406	0.485	0.025
	August 27, 2002	0.079	0.430	0.081	0.423	0.109	0.350
	September 16, 2002	0.112	0.344	0.184	0.216	0.099	0.374
Mixed Conv. (24 Fields)	July 30, 2002	<0.001	0.980	0.176	0.040	<0.001	0.981
	August 27, 2002	0.033	0.392	0.019	0.512	0.033	0.389
	September 16, 2002	0.013	0.592	0.003	0.778	0.014	0.581
B3945 (24 Fields)	July 30, 2002	<0.001	0.728	0.026	0.449	0.005	0.739
	August 27, 2002	<0.001	0.898	<0.001	0.987	0.001	0.882
	September 16, 2002	<0.001	0.947	0.002	0.817	<0.001	0.873
B4811 (41 Fields)	July 30, 2002	<0.001	0.960	0.071	0.091	0.070	0.092
	August 27, 2002	0.001	0.830	0.014	0.460	0.006	0.621
	September 16, 2002	0.003	0.726	0.001	0.833	0.001	0.832

Table 4.4 R^2 values for models correlating recoverable sucrose content to differences in spectral indexes over two dates in a season. Differences are given for the months of July (07), August (08), and September (09).

Variety	Difference Dates	Δ–NDVI		Δ–Green NDVI		Δ -SAVI	
		R^2	Pr.	R^2	Pr.	R^2	Pr.
Mixed Rhizo. (10 Fields)	Δ(07–08)	0.342	0.075	0.253	0.137	0.476	0.163
	Δ(08–09)	0.204	0.190	0.004	0.851	0.393	0.052
	Δ(07–09)	0.412	0.045	0.318	0.089	0.300	0.101
Mixed Conv. (24 Fields)	Δ(07–08)	0.017	0.543	0.186	0.035	0.015	0.568
	Δ(08–09)	<0.001	0.975	0.004	0.745	<0.001	0.982
	Δ(07–09)	0.012	0.597	0.189	0.033	0.011	0.620
B3945 (24 Fields)	Δ(07–08)	<0.002	0.84	0.012	0.53	0.001	0.87
	Δ(08–09)	<0.001	0.93	0.004	0.76	<0.001	0.94
	Δ(07–09)	<0.002	0.83	0.004	0.67	0.001	0.86
B4811 (41 Fields)	Δ(07–08)	<0.001	0.91	0.155	0.01	0.138	0.016
	Δ(08–09)	<0.001	0.97	0.012	0.39	0.0102	0.48
	Δ(07–09)	<0.001	0.92	0.028	0.29	0.0260	0.30

4.1.1 Linear Regression Analyses for Mixed Rhizomania Class

Linear regression analysis was performed for the Mixed Rhizomania class of sugarbeet varieties. Following are the results presented for each index and linear regression models between these indices and the quality of fields planted to multiple rhizomania tolerant varieties.

4.1.1.a. NDVI

Linear regression analyses models between NDVI and Recoverable Sucrose showed correlation on only the July image date at the significance level of 0.05. The correlation coefficient was 0.487. No other model shows a statistical link between the NDVI and recoverable sucrose content. The average NDVI were 0.39, 0.50 and 0.40 on July 30th, August 27th and September 16th, respectively (Table 4.1). Fig 4.1 shows the scatter-gram of the data for these image dates.

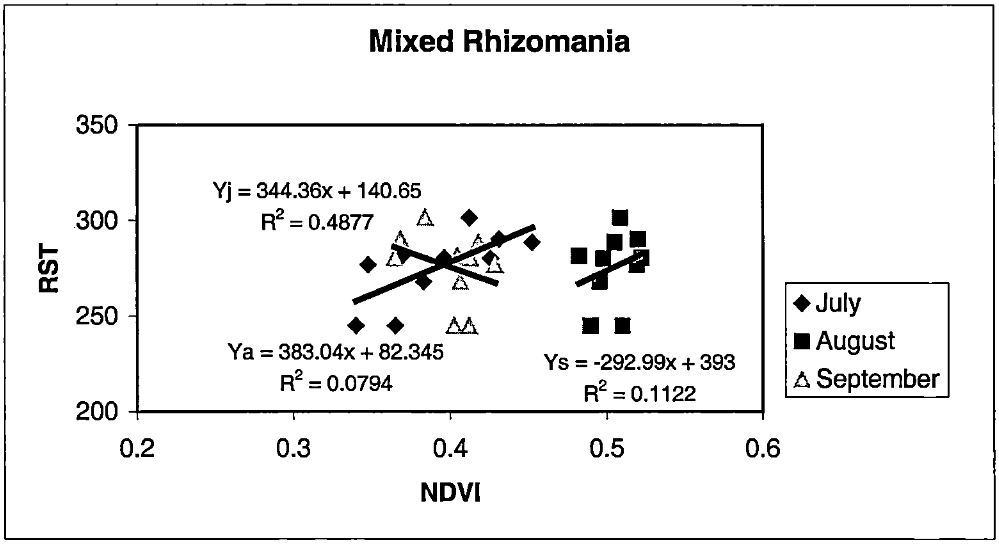

Fig. 4.1 Result of linear regressions, between the NDVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for fields planted to mixed Rhizomania tolerant varieties.

4.1.1.b Temporal changes in NDVI and Sugarbeet quality

This analysis was performed to investigate the model relationship between changes in NDVI over time, with recoverable sucrose. One model showed some correlation. The correlation coefficient R^2, for the model involving change in the NDVI for July to September with recoverable sucrose was 0.412 (Table 4.4). Mean differences in NDVI were 0.11, -0.10 and 0.016 (Table 4.2). The results of linear regression for the difference between indexes on two different dates over the season are shown in Fig. 4.2.

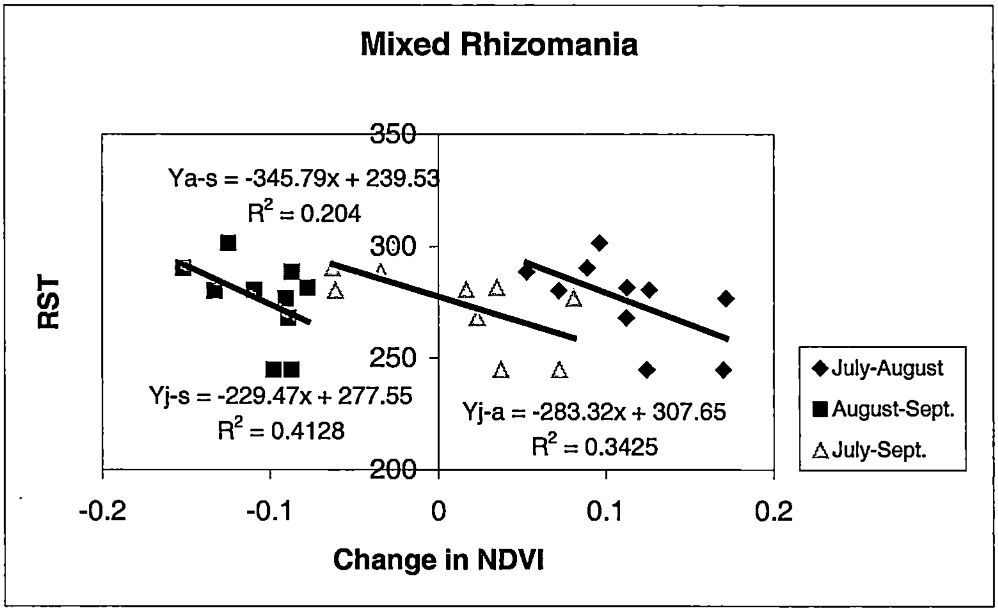

Fig. 4.2 Results of linear regressions between the differences in NDVI for two dates in the season and RST (pounds of sucrose recoverable per ton of sugarbeet) for fields planted to mixed Rhizomania tolerant varieties.

4.1.2.a. Green NDVI

Sugarbeet growers have long associated a visible "yellowing" of the canopy in sugarbeets with high sucrose concentrations. This visible effect suggests the use of an index that includes a green band measurement. The linear regression models between the green NDVI on individual dates and recoverable sugar content showed no correlation for the mixed rhizomania class. The average values of green NDVI were 0.33, 0.57 and 0.37 on July 30th, August 27th and September 16th, respectively (Table 4.1). Fig 4.3 shows the scatter of the data for the Green NDVI for the three dates.

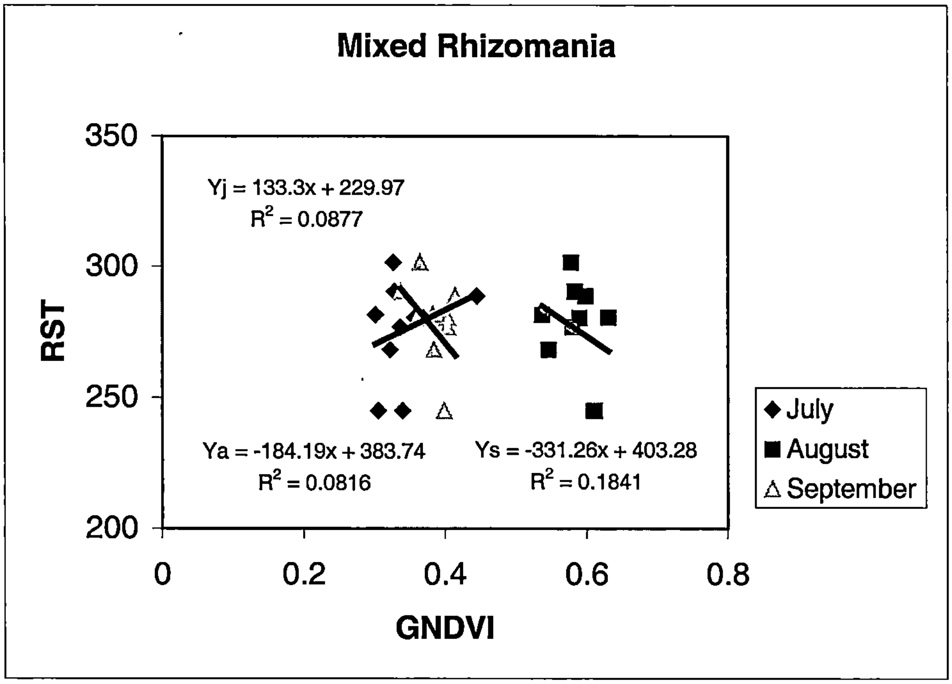

Fig. 4.3 Results of linear regressions between the Green NDVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for fields planted to mixed Rhizomania tolerant varieties.

4.1.2.b. Temporal changes in Green NDVI and Sugarbeet quality

Models for difference in GNDVI showed no statistically significant correlation (Table 4.3) at the significance level of 0.05. Mean difference in green NDVI for July and August was 0.24. For August to September it was, -0.19 and 0.04 for July and September. The results of linear regression for the difference between indexes on two different dates in the season are shown in Fig. 4.4.

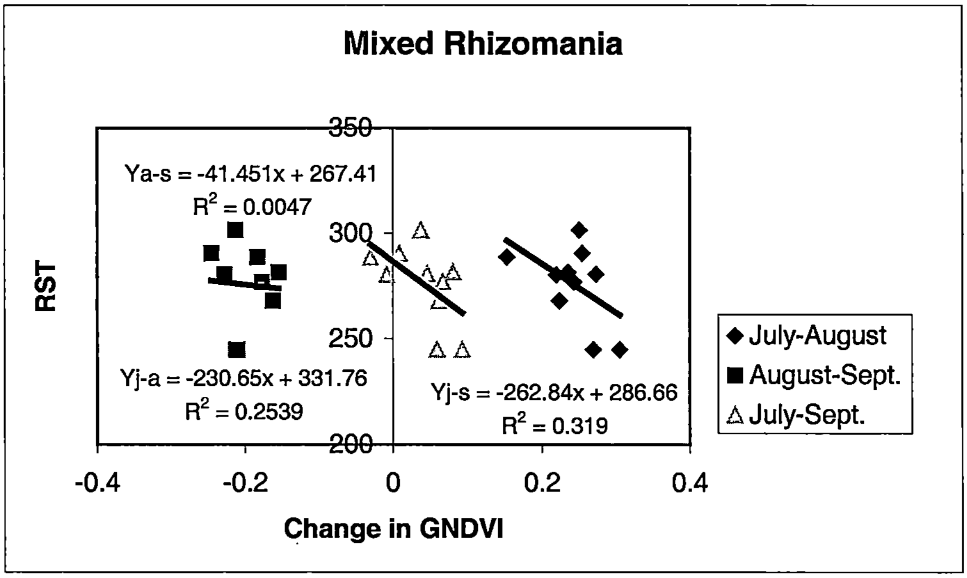

Fig. 4. 4 Results of linear regressions between differences in the Green NDVI for two dates in the season and RST (pounds of sucrose recoverable per ton of sugarbeet) for fields planted to mixed Rhizomania tolerant varieties.

4.1.3.a. SAVI

A SAVI, soil adjusted vegetation index is a modification of the NDVI to account for the soil background effects. It uses NIR and red bands of the spectrum. Values of R^2 for the linear regression model for the SAVI on July 30, was 0.48 with a significance level of 0.05 (Table 4.3). On the subsequent dates of August 27, and September, the models for the SAVI were not significant. The average SAVI were 0.49, 0.65 and 0.52 on July 30th, August 27th and September 16^{th}, respectively (Table 4.1).

4.1.3.b Temporal changes in SAVI and Sugarbeet quality

This analysis was performed to investigate the statistical link between the difference in SAVI derived from two different dates and the recoverable sucrose content. None of the models using a change in SAVI for any time interval showed significant correlation (Table 4.3). Although the scatter-grams seem to indicate a clear negative slope in the relationship, the small number of available fields in this class, makes it difficult to establish the statistical link. Mean difference in SAVI for July and August was 0.16. For August to September it was, -0.13 and 0.04 for July and September.

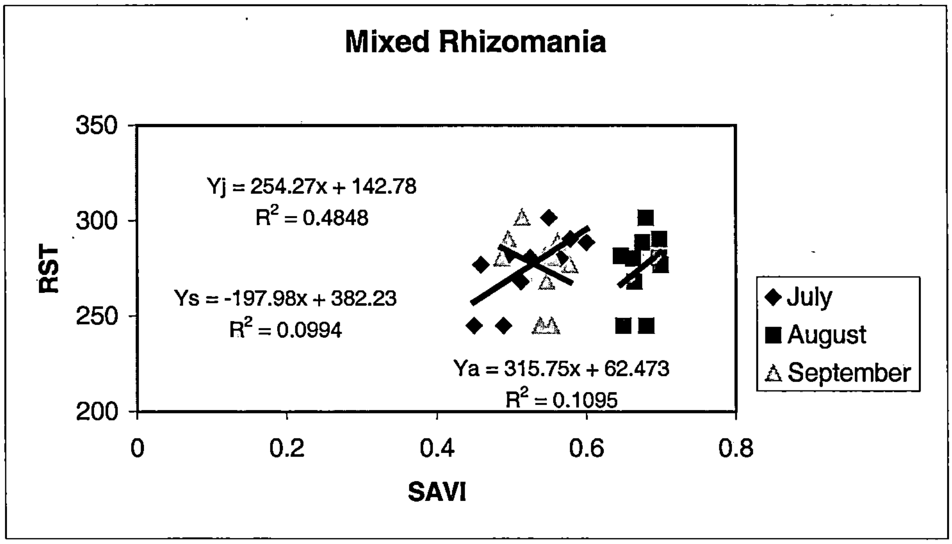

Fig. 4.5 Results of linear regressions between the SAVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for three dates for fields planted to mixed Rhizomania tolerant varieties.

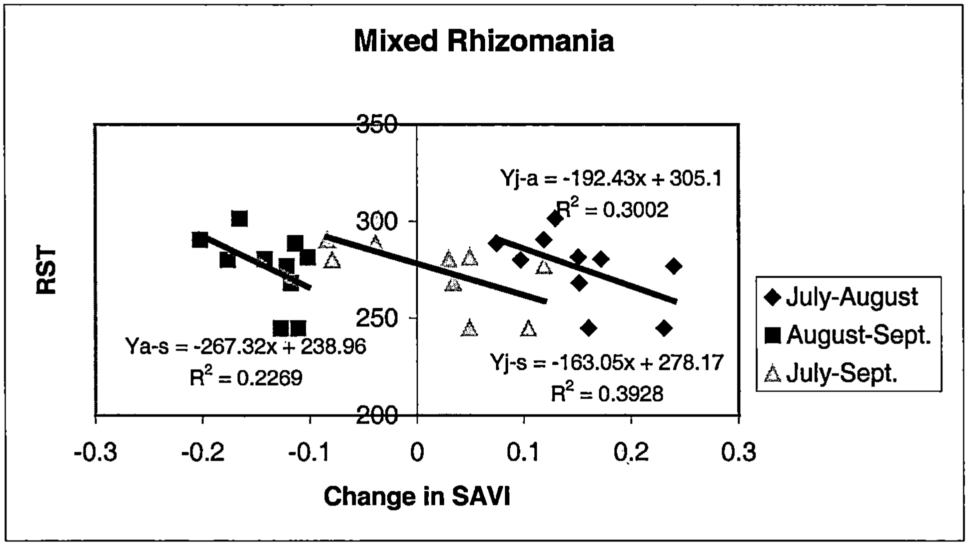

Fig. 4.6 Results of linear regressions between differences in the SAVI for two dates in the season and RST (pounds of sucrose recoverable per ton of sugarbeet) for fields planted to mixed Rhizomania tolerant varieties.

4.2.1 Linear Regression Analyses for a Mixed Conventional Class

Linear regression analysis was performed for a Mixed Conventional class of sugarbeet varieties, which do not show tolerance to the disease rhizomania. The following are the results presented for each index and the differences in indices over time.

4.2.1.a. NDVI

Linear regression analyses between NDVI and recoverable sucrose showed no statistical significance at a level of 0.05 for models relating RST and canopy indices on a single date (Table 4.3). The mean values of NDVI were 0.42, 0.52 and 0.39 on July 30th, August 27th and September 16th respectively (Table 4.1). Fig 4.7 shows the scatter-gram of the data.

4.2.1.b Temporal changes in NDVI and Sugarbeet quality

This analysis was performed to investigate the model relationship for a change in NDVI, with recoverable sucrose. None of the models for this variety of class showed statistical significance. (Table 4.4). Mean differences in NDVI were 0.09, -0.12 and 0.03 (Table 4.2). The results of linear regression for the difference between indexes on two different dates over the season are shown in Fig. 4.8.

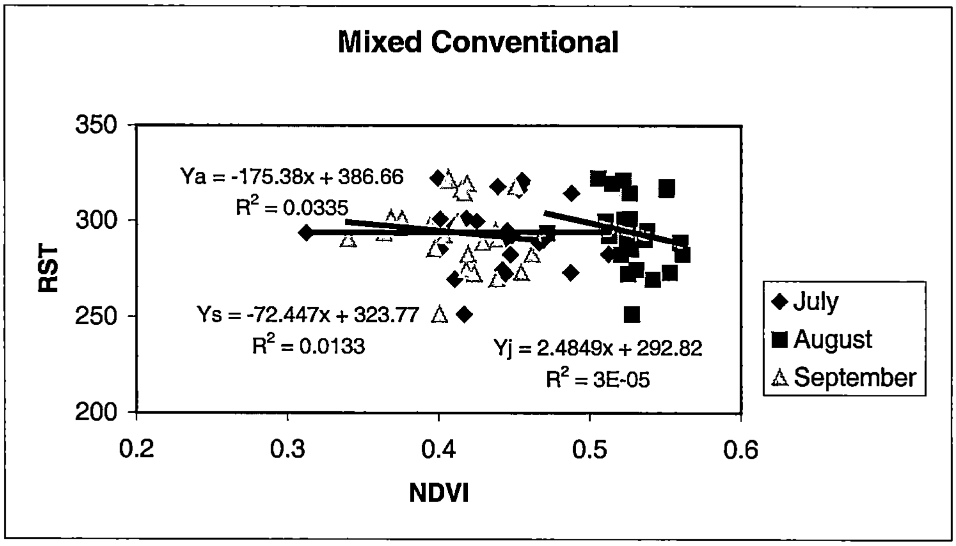

Fig. 4.7 Results of regressions, between the NDVI for the fields planted to mixed conventional varieties and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates.

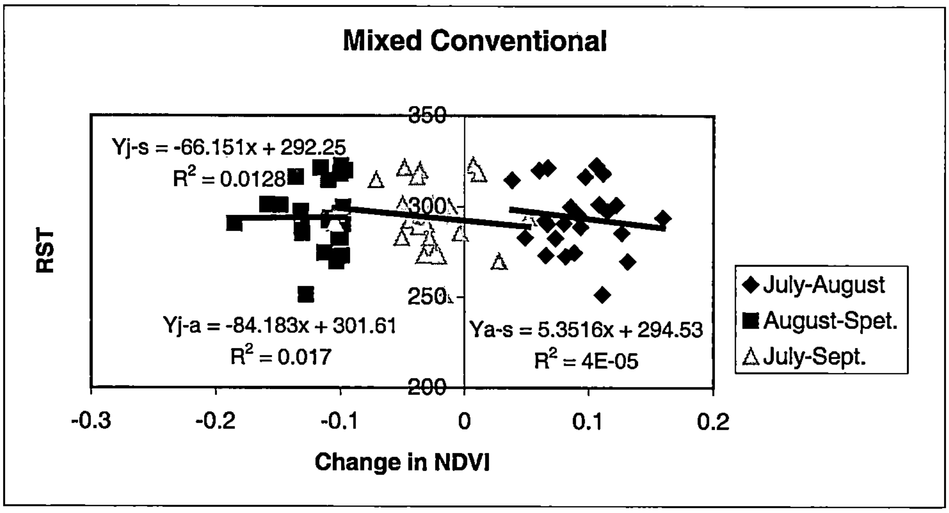

Fig. 4.8 Results of regression between difference in NDVI for two dates in the season for the Mixed Conventional varieties of Sugarbeet and RST (pounds of sugar recoverable per ton of sugarbeet).

4.2.2.a. Green NDVI

The linear regression models between the Green NDVI and recoverable sugar content showed correlation only on the July 30 image date. The correlation coefficient was 0.176, at the significance level of 0.05 (Table 4.4). The average green NDVI were

0.36, 0.59 and 0.38 on the July 30th, August 27th and September 16th, respectively (Table 4.1). Fig 4.9 shows the scatter of the data for Green NDVI for the three dates.

4.2.2.b. Temporal changes in Green NDVI and Sugarbeet quality

Models for difference in GNDVI from July to August and July to September showed some correlation. The coefficients of correlation were 0.186 and 0.189 respectively. Mean difference in green NDVI for July was 0.22. For August to September it was, -0.21 and 0.01 for July and September. The results of linear regression for the difference between indexes on two different dates in the season are shown in Fig. 4.10.

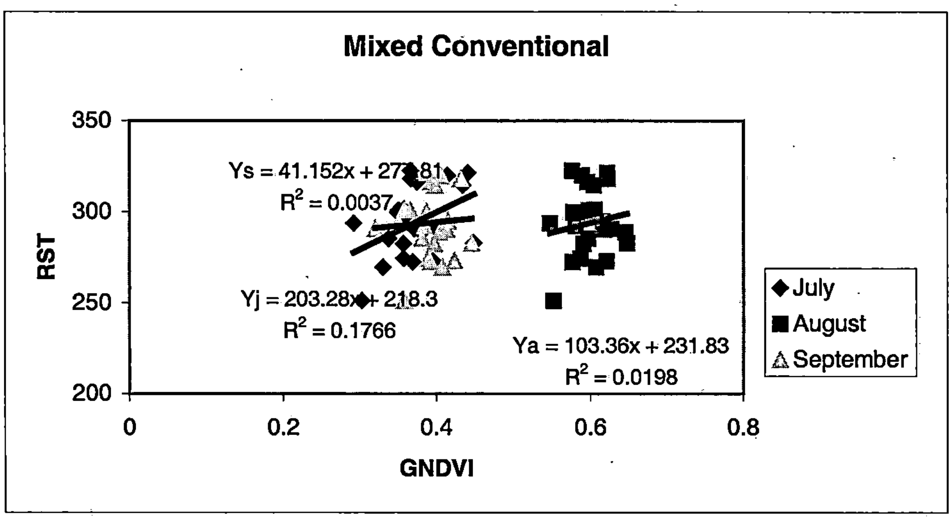

Fig. 4.9 Results of regressions, between the Green NDVI for the fields planted to mixed conventional varieties and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates.

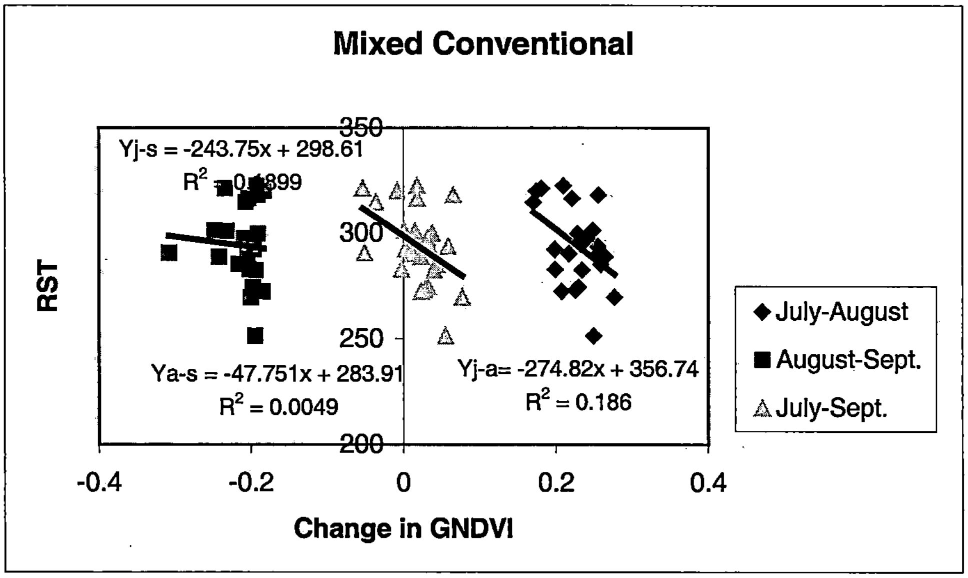

Fig. 4.10 Results of regression between difference in Green NDVI for two dates in the season for the Mixed Conventional varieties of Sugarbeet and RST (pounds of sugar recoverable per ton of sugarbeet).

4.2.3.a. SAVI

A SAVI, soil adjusted vegetation index is a modification in NDVI to account for soil background effects. It uses NIR and red bands of the spectrum. The linear regression models using SAVI on single dates showed no statistical correlation (Table 4.3). The average SAVI were 0.57, 0.69 and 0.53 on July 30th, August 27th and September 16th, respectively. Fig 4.11 shows the scatter of the data for SAVI for the three dates.

4.2.3.b Temporal changes in SAVI and Sugarbeet quality

This analysis was performed to investigate the statistical link between the difference in SAVI derived for two different times and the recoverable sugar content. These regressions showed no correlation at significance level 0.05 (Table 4.4). Mean difference in SAVI was 0.12 between July and August. It was -0.16 for between August and September and 0.03 for the July and September. The results of linear regression for the difference between indexes on two different dates in the season are shown in Fig. 4.12

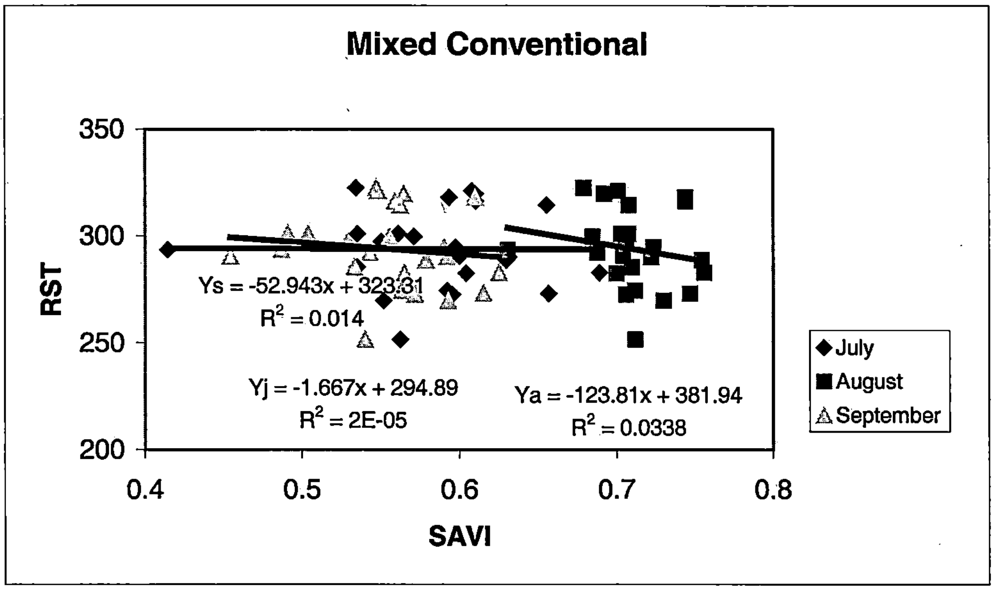

Fig. 4.11 Results of regression, between the SAVI for the fields planted to mixed conventional varieties and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates.

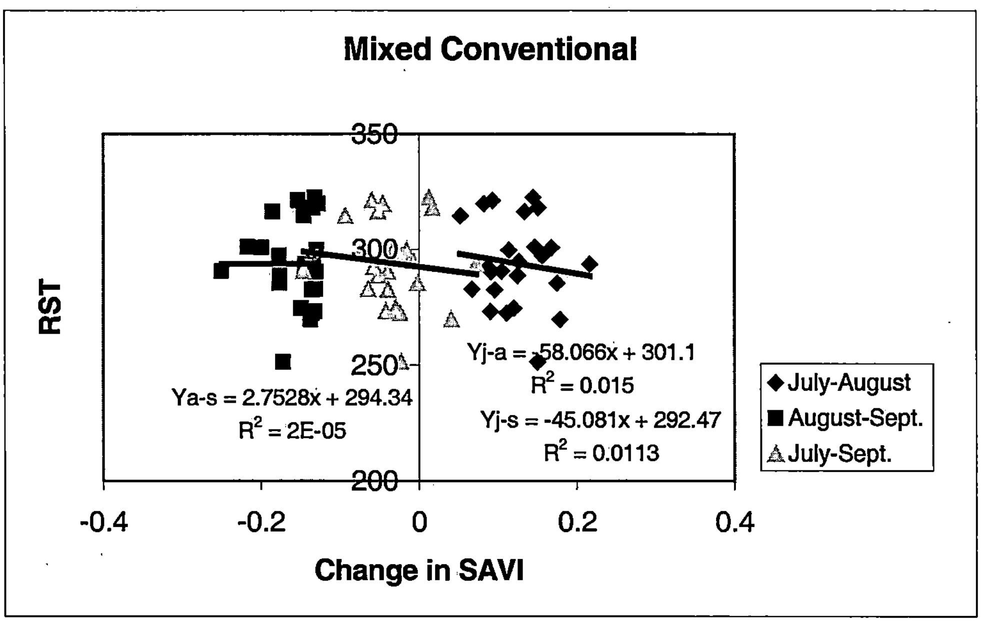

Fig. 4.12 Results of regression between difference in SAVI for two different dates in the season for the Mixed Conventional varieties of Sugarbeet and RST (pounds of sugar recoverable per ton of sugarbeet).

4.3.1 Linear Regression Analyses for B3945 Class

Linear regression analysis was performed for a group of fields planted to a common conventional variety named B3945. Following are the results presented for each index and temporal change in the indices.

4.3.1.a. NDVI

Linear regression models between the NDVI on individual date and recoverable sucrose showed no correlation, at the significance level of 0.05. The average NDVI values were 0.40, 0.48 and 0.37 on July 30th, August 27th and September 16th, respectively (Table 4.1). Fig 4.13 shows the scatter of the data.

4.3.1.b Temporal changes in NDVI and Sugarbeet quality

This analysis investigated the model relationships for temporal changes in the NDVI, with recoverable sucrose. Mean differences in NDVI were 0.8, -0.11 and -0.03 (Table 4.2). The results of linear regression for the difference between this index on two different dates over the season are shown in Fig. 4.14. None of the models using a change in NDVI for any of the time intervals showed statistical significance in this data set.

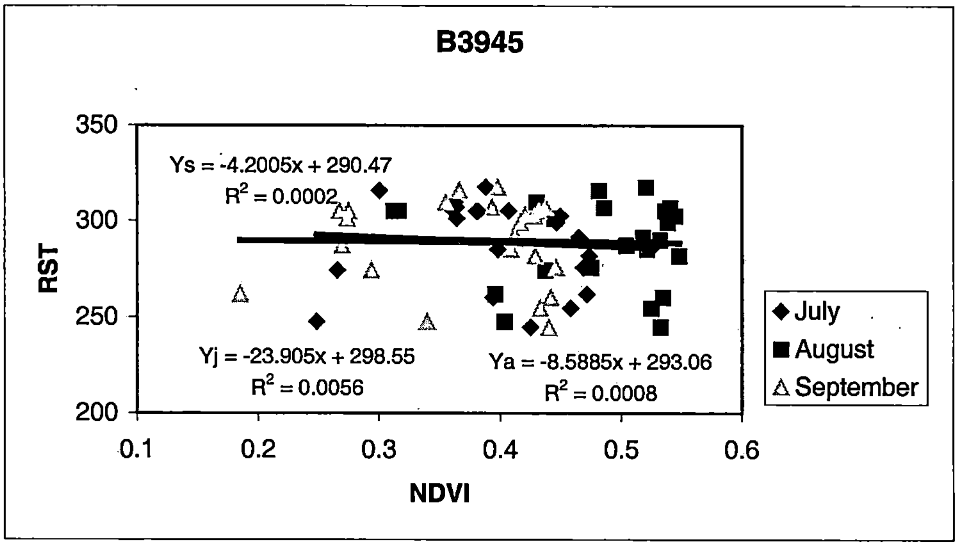

Fig. 4.13 Results of linear regressions, between the NDVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for the fields planted to the variety B3945.

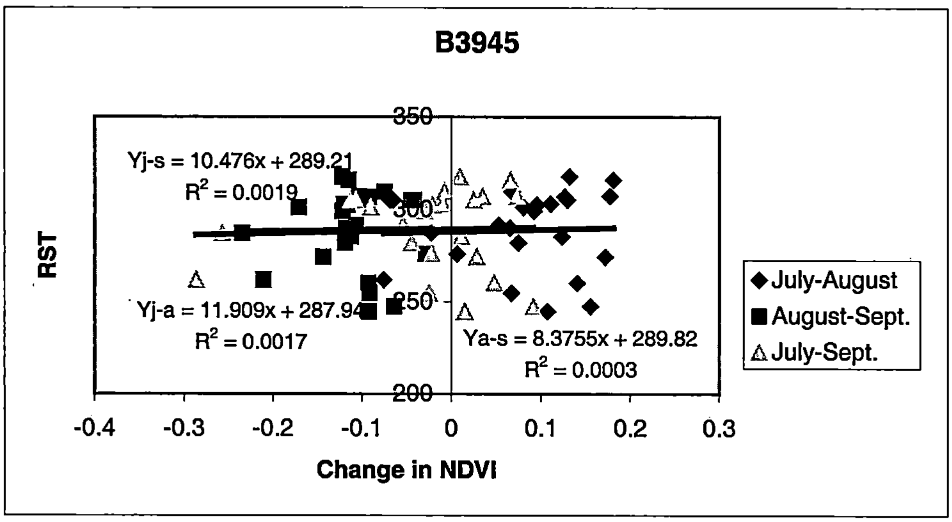

Fig. 4.14 Results of linear regressions between difference in NDVI and RST (pounds of sugar recoverable per ton of sugarbeet) for two different dates in the season for the B-3945 variety of Sugarbeet.

4.3.2.a. Green NDVI

Linear regression models between the Green NDVI on individual dates and recoverable sucrose content in field planted to B3945 showed no correlation. The average values of green NDVI were 0.38, 0.58 and 0.34 on July 30th, August 27th and September

16th, respectively (Table 4.1). Fig 4.15 shows the scatter of the data for the Green NDVI for the three dates.

4.3.2.b. Temporal changes in Green NDVI and Sugarbeet quality

Models for change in GNDVI showed no correlation to RST in the B3945 fields. Mean change in green NDVI for July and August was 0.20. For August to September it was -0.21 and 0.01 for July and September (Table 4.2). The scatter-gram for the difference between indices on two different dates in the season is shown in Fig. 4.16.

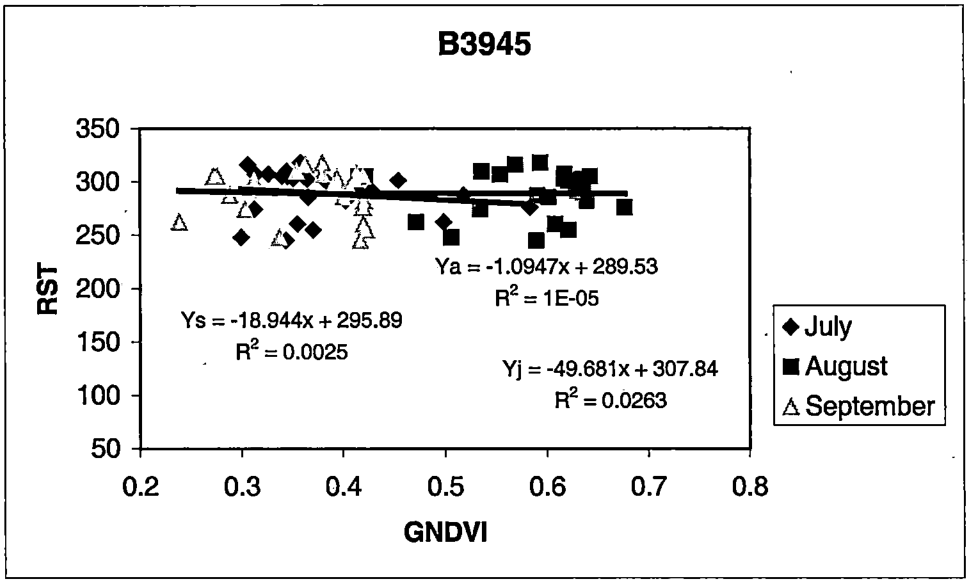

Fig. 4.15 Results of linear regressions, between the NDVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for the fields planted to B3945 variety.

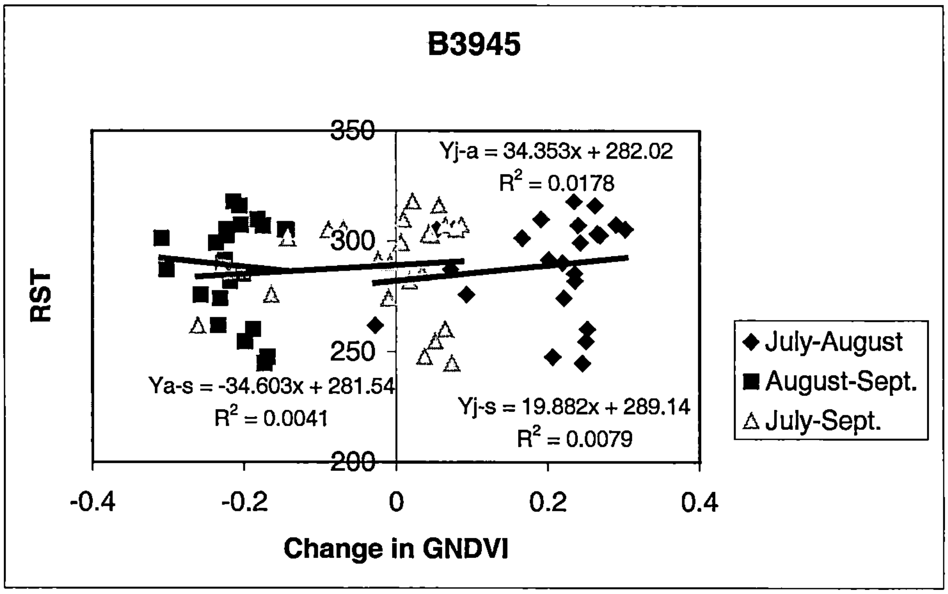

Fig. 4.16 Results of linear regression between change in Green NDVI and RST (pounds of sugar recoverable per ton of sugarbeet) for two dates in the season for the B-3945 variety of Sugarbeet.

4.3.3.a. SAVI

A SAVI, soil adjusted vegetation index is a modification of the NDVI to account for the soil background effects. It uses NIR and red bands of the spectrum. No correlations were exhibited by any of the models for single dates. The average SAVI values were 0.53, 0.64 and 0.50 on July 30th, August 27th and September 16th, respectively.

4.3.3.b Temporal changes in SAVI and Sugarbeet quality

This analysis was performed to investigate the statistical link between the difference in SAVI derived from two different dates and recoverable sucrose content. No statistical correlation was exhibited by any of the models tested for this index in this variety. Mean difference values for SAVI was 0.16 for the time interval July to August.

For August to September and July to September the changes in values of SAVI were -0.13 and 0.02 respectively.

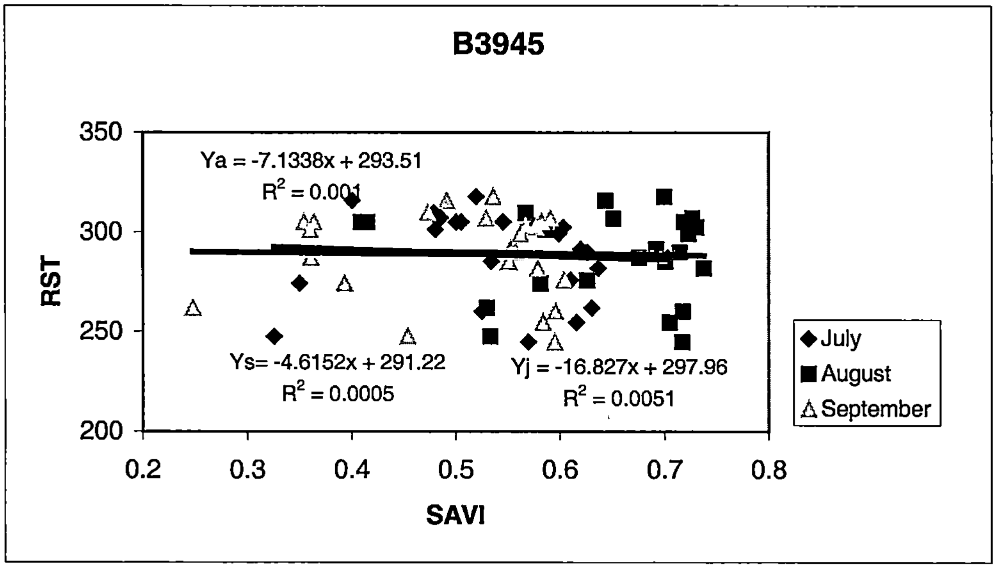

Fig. 4.17 Result of linear regressions, between the NDVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for the fields planted to B3945 variety.

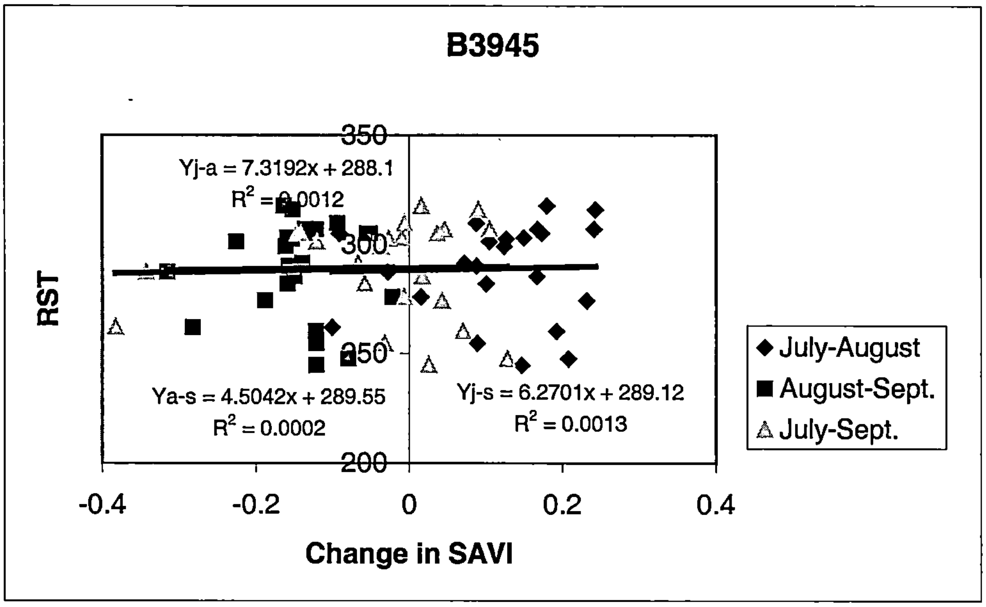

Fig. 4.18 Result of linear regressions between difference in SAVI and RST (pounds of sugar recoverable per ton of sugarbeet) on two different dates in the season for the B-3945 variety of Sugarbeet.

4.4.1 Linear Regression Analyses for the variety B4811

Linear regression analysis was performed for a group of fields planted to a pure strain of a rhizomania tolerant variety, B4811. Following are the results presented for each index and the changes in each index over time.

4.4.1.a. NDVI

Linear regression analyses between NDVI and Recoverable Sucrose showed no correlation on any of individual dates. Mean NDVI were 0.40, 0.49 and 0.39 on July 30th, August 27th and September 16th respectively (Table 4.1). Fig 4.19 shows the scatter-gram of the data.

4.4.1.b Temporal changes in NDVI and Sugarbeet quality

None of the models showed correlation to change in NDVI over time to recoverable sucrose content. Mean differences in NDVI were 0.09, -0.10 and -0.01 (Table 4.2). Scatter diagrams for the linear regressions for the change in index values on two different dates over the season are given in Fig. 4.20.

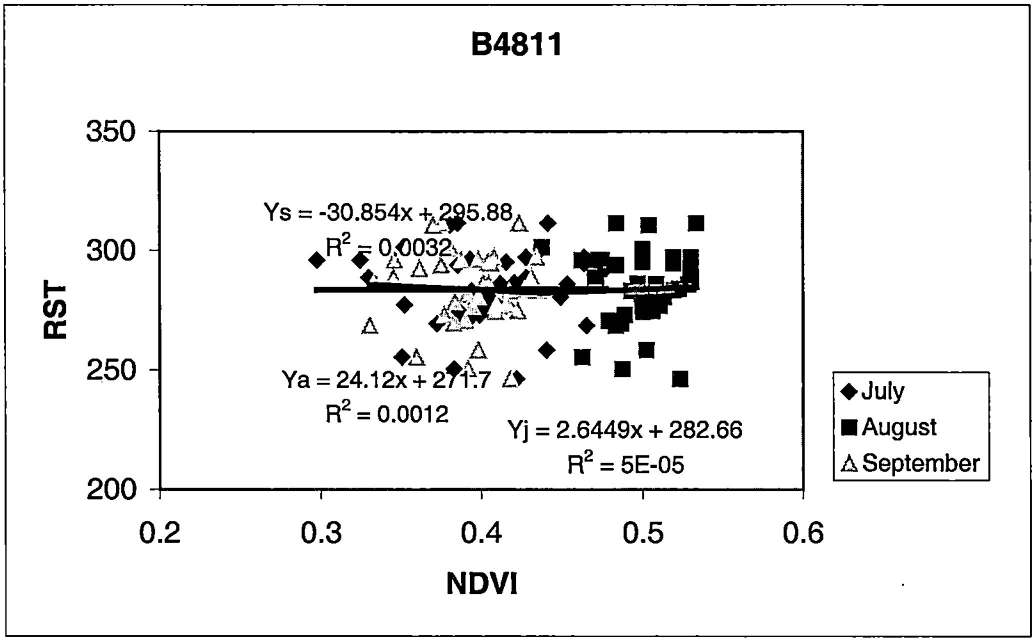

Fig. 4.19 Results of linear regressions, between the SAVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for the fields planted to B4811 variety.

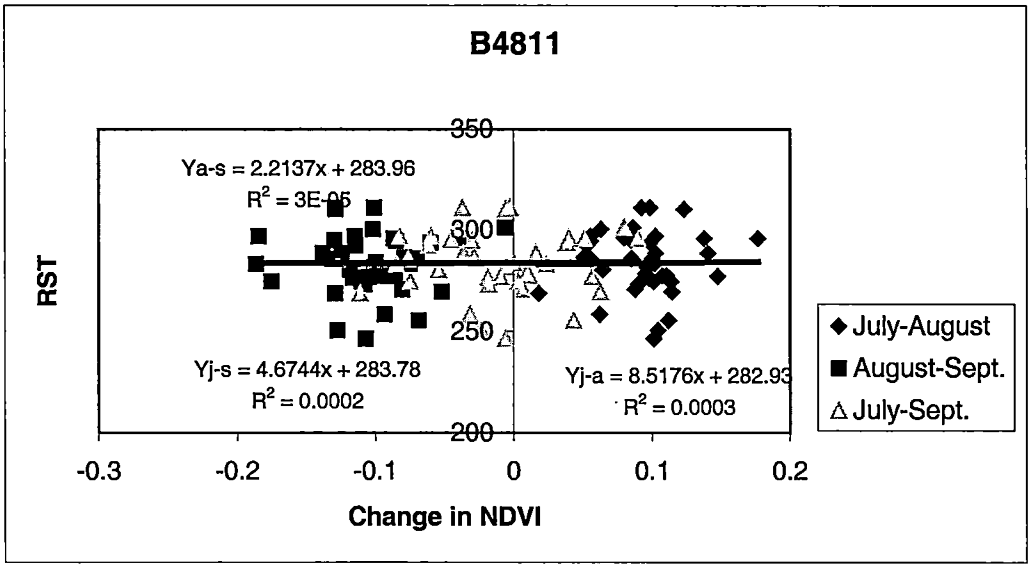

Fig. 4.20 Results of linear regressions between difference in the NDVI and RST (pounds of sugar recoverable per ton of sugarbeet) for two different dates in the season for B4811 variety of sugarbeet.

4.4.2.a. Green NDVI

Linear regression models between the green NDVI and recoverable sugar content showed no correlation in the variety B4811. The scatter-gram of data is shown in Fig. 4.21.

4.4.2.b. Temporal changes in Green NDVI and Sugarbeet quality

A model for difference in GNDVI from July to August showed weak correlation. The coefficient of correlation was 0.155 but was significant at the 0.05 level (Table 4.4). The results of linear regression for the difference between indexes on two different dates in the season are shown in Fig. 4.22. The models from July to September and August to September did not indicate statistically significant links.

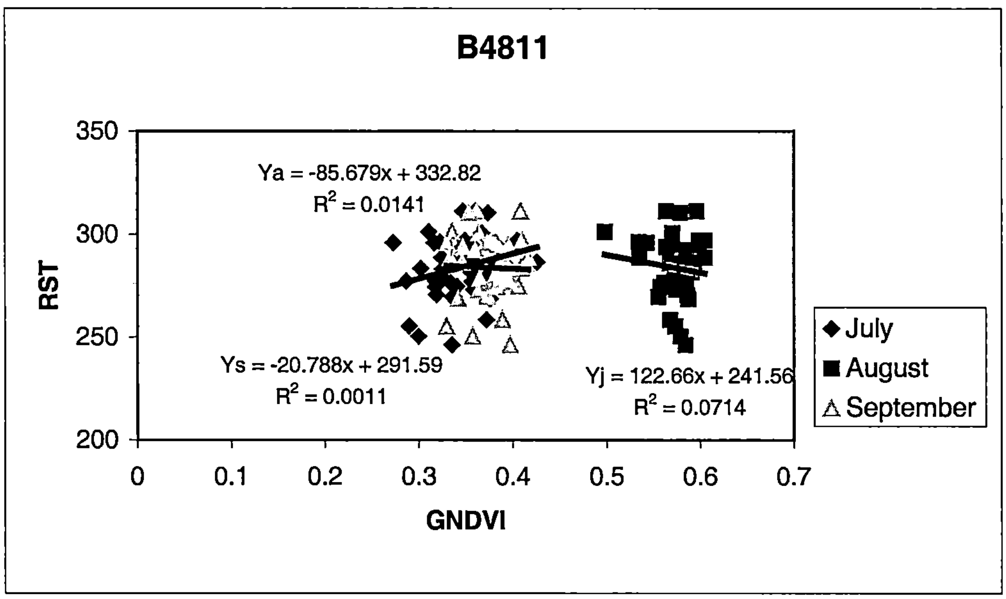

Fig. 4.21 Results of regression, between the Green NDVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for the fields planted to B4811 variety.

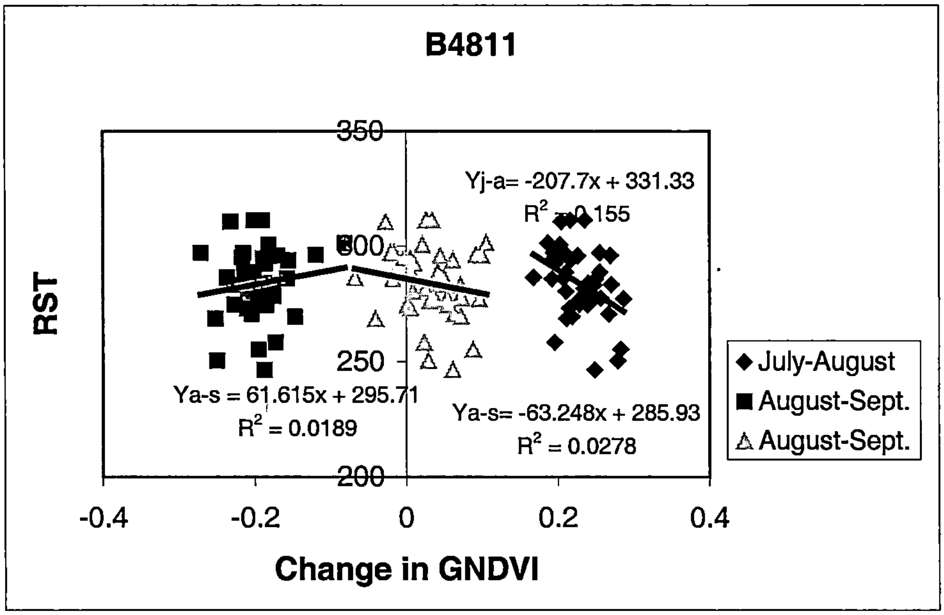

Fig. 4.22 Results of regression between difference in Green NDVI and RST (pounds of sugar recoverable per ton of sugarbeet) for two different dates in the season for the B-4811 variety of Sugarbeet.

4.4.3.a. SAVI

The linear regression models for SAVI showed no statistical correlation for individual dates for variety B4811. Fig 4.23 shows the scatter of the data for the three dates.

4.4.3.b Temporal changes in SAVI and Sugarbeet quality

This analysis was performed to identify possible statistical links between the difference in SAVI, derived for two different times, and the recoverable sucrose content. The R^2 for the model for the change in SAVI for July to August was 0.138 (Table 4.3). This model showed statistical significance. Other models did not. Mean difference in SAVI from July to August was 0.30. It was -0.25 from August to September and 0.04 from July to September (Table 4.2). The results of linear regression for the difference between indices on two different dates over the season are shown in Fig. 4.24.

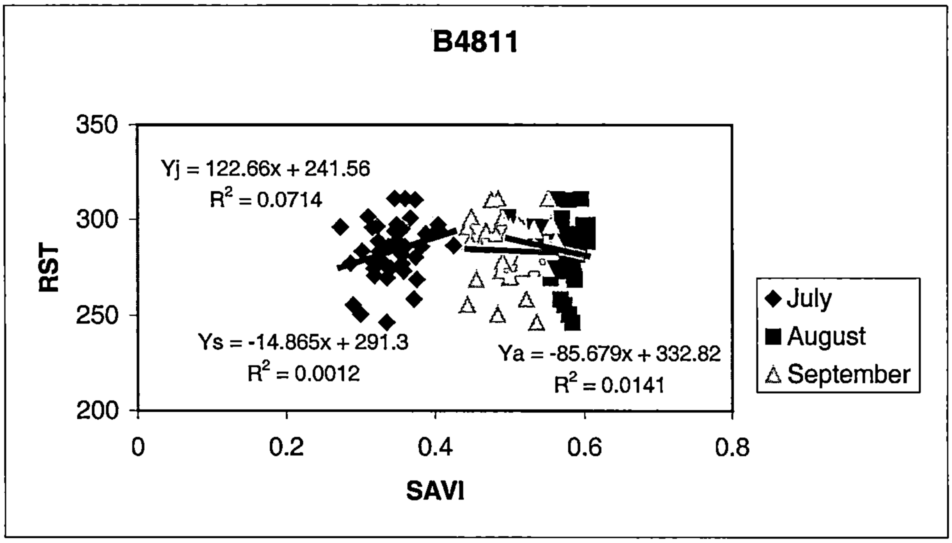

Fig. 4.23 Results of regression between the NDVI and RST (pounds of sucrose recoverable per ton of sugarbeet) for the three dates for the fields planted to B4811 variety.

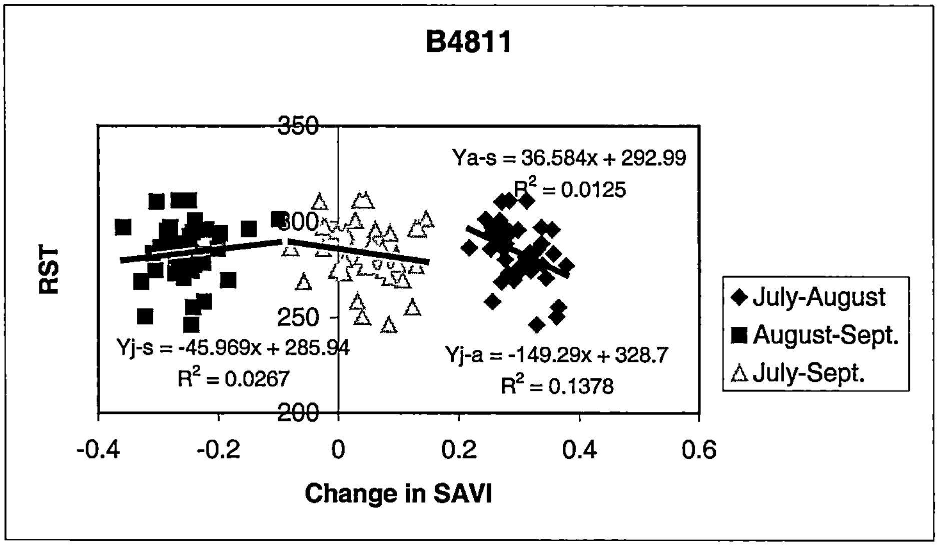

Fig. 4.24 Results of linear regressions between the difference in SAVI and RST (pounds of sugar recoverable per ton of sugarbeet) for two different dates in the season for the B-4811 variety of sugarbeet.

4.5 Multiple Linear Regression Models

The purpose of using multiple regression analysis was to learn more about the relationship between the sucrose content in sugarbeets and changes in vegetation indexes over two different time intervals in the season. Combine effect of changes in more than one vegetation index over the same time interval on sucrose content was also studied.

Each index was tested in a two-parameter model in which the first parameter, or independent variable, was the change in the index value from July to August. The second parameter was the change in the same index from August to September. Next a three parameter model was tested in which the parameters were represented by each of the three indices for the overall time interval from July to September. Finally, a six-parameter model was tested that considered each of the three models for each of the two time periods, July to August, and August to September.

4.5.1 Multiple Linear Regression Models for Mixed Rhizomania

Multi-parameter models between change in vegetation indices and recoverable sucrose for two time periods in the season showed no statistical link for the group of fields planted to mixed rhizomania tolerant varieties.

4.5.2 Multiple Linear Regression Models for Mixed Conventional

Two parameter models with change in NDVI from July to August and change in NDVI from August to September considered as two independent variables showed no statistically significance at 0.05 level. Similarly, models considering change in Green NDVI and SAVI from July to August and August to September exhibited no statistically significant correlation.

A three-parameter model, considered changes in three individual indices over the time period July to September, and showed a statistically significant correlation at the 0.05 level. The coefficient of correlation was 0.471.

A Six-parameters model considering the changes in individual vegetation index, from July to September resulted in a statistically significant correlation. The correlation coefficient was 0.635.

4.5.3. Multiple Linear Regression Models for B3945

None of the multi-parameter models, including two-parameter, three-parameter, and six-parameter models between change in vegetation indices and recoverable sucrose produced a statistically significant correlation.

4.5.4 Multiple Linear Regression Models for B4811

Two parameter models considering change in Green NDVI from July to August and change in Green NDVI from August to September showed low correlation. However, this model appeared to have statistical significance. The coefficient of correlation value was 0.16. A six-parameter model considering the changes in individual vegetation index, from July to September gave a statistically significant correlation. The coefficient of correlation was 0.33.

Correlation coefficients for various multiple linear regression models of relationship between vegetation indexes and quality data for each variety are shown in Table 4.5.

Table 4.5 Results of Multiple Linear Regressions

Variety class	(NDVI_8_7)* x (NDVI_9_8)	(GNDVI_8_7)**x (GNDVI_9_8)	(SAVI_8_7)*** x (SAVI_9_8)	(NDVI_9_7)**** x (GNDVI_9_7) x (SAVI_9_7)	All indices*****
Mix. Rhizo.	$R^2 = 0.398$ Pr.=0.168	$R^2 = 0.329$ Pr.=0.246	$R^2 = 0.381$ Pr.=0.187	$R^2 = 0.698$ Pr.=0.053	$R^2 = 0.909$ Pr.=0.107
Mixed Conv.	$R^2 = 0.018$ Pr.=0.828	$R^2 = 0.231$ Pr.=0.063	$R^2 = 0.016$ Pr.=0.846	$R^2 = 0.471$ Pr.=0.005	$R^2 = 0.635$ Pr.=0.044
B3945	$R^2 = 0.002$ Pr.=0.979	$R^2 = 0.024$ Pr.=0.775	$R^2 = 0.001$ Pr.=0.986	$R^2 = 0.064$ Pr.=0.713	$R^2 = 0.209$ Pr.=0.619
B4811	$R^2 = <0.001$ Pr.=0.994	$R^2 = 0.159$ Pr.= 0.037	$R^2 = 0.139$ Pr.=0.056	$R^2 = 0.122$ Pr.=0.182	$R^2 = 0.332$ Pr.=0.025

* Two parameters model using change in NDVI from July to August and change in NDVI from August to September.
** Two parameters model using change in GNDVI from July to August and change in GNDVI from August to September.
*** Two parameters model using change in SAVI from July to August and change in SAVI from August to September.
**** Three parameters model using change in NDVI from July to September, change in GNDVI from July to September, and change in SAVI from July to September.
***** Six parameter model using change in NDVI from July to August and change in NDVI from August to September, change in GNDVI from July to August and change in GNDVI from August to September and change in SAVI from July to August and change in SAVI from August to September.

4.6 Discussion

4.6.1 Vegetation Indices: Temporal changes and recoverable sucrose content.

A common trend can be visually observed for all of the graphical results for temporal changes in vegetation indices for each class of sugarbeets. All the vegetation indices for all the classes of sugarbeets have higher values for the month of August than those for July.

Temporal changes in individual vegetation indices over the three time intervals in the season were observed for three time intervals. The first interval was from July to August, the second was from August to September and the third interval was from July to

September. From, July to August, the changes in the indices were positive. In the second time interval, from August to September, the difference became negative. The possible causes for the higher NIR reflectance in the first interval and an exactly opposite trend in the later stage is discussed below.

NIR reflectance values are a part of each of the indices. The changes in indices calculated over these periods, can be associated with plant behavior. The tendency of the sugarbeet plant is that it initially produces rapid vegetative growth and then stores sucrose in the later stage of growth. It is known that high NIR reflectance is associated with deep green, vigorous canopy. In the initial period the rapid growth of leaves may cause increasing NIR reflectance, and hence the higher indices. At some point these values are reduced as the crop changes physiologically. Leaf growth slows as nitrogen is exhausted and the visible wavelength reflectance increases. In this later period the leaves often tend to be greenish yellow or yellow. This stress also can be associated with lower NIR reflectance. The greenish yellow canopy has been associated with higher sucrose content (Humburg, 2002).

Another reason for increased NIR reflectance could be weed growth during the season. It may contribute to the enhanced NIR reflectance.

Biological activities in the soil after rains may cause mineralized nitrogen get released to the sugarbeet plant. This may result in increased foliage growth for some time.

Canopy reflectance may also depend on the population. A sparse population can mean additional nitrogen available to remaining sugarbeets. This may result in a vigorous, deep green canopy and subsequently higher NIR reflectance. Conversely, if the population is low enough to expose significant areas of soil surface, the measured reflectance will be much lower in the NIR, lowering the values of the indices

The rapid growth of plants minimizes the soil exposure to the satellite sensor. On the first date, July 30, 2002, the satellite sensor may have been exposed to a greater amount of mixed reflectance of both soil and plant. From July to August the value of all of the indices may have increased as the exposure of soil was reduced. Indices generally decreased on the last date. This may be due to a reduction in foliage growth, and a lower NIR reflectance in existing canopy due to nitrogen stress as the crop exhausted the existing supply of nitrogen.

Lower NIR reflectance perhaps can also be associated with rhizomania, a common disease in sugarbeets in the southern part of Minnesota. The symptoms of this disease can normally be seen in fields as strips or patches of lighter foliage within an otherwise healthy crop. Lighter or yellowish canopy can result in higher visible reflectance and subsequently higher vegetation indices. The disease stress may also be associated with lower NIR reflectance. Sugarbeets affected by rhizomania result in smaller root in size and lower recoverable sucrose concentrations. The effect of the disease is exactly the opposite of the expected effect in healthy sugarbeets. Fields unaffected by the disease would have had green canopy and higher NIR reflectance, and in turn, higher index values. Unaffected fields still might have yielded higher recoverable sucrose concentrations since they were not stressed by the disease.

We had no information regarding the health of the crop in each field. If the database had specified ground truth, such as problems experienced by the crop if any, it might allow selection of healthy and normal fields, and reduce scatter in the data. Occurrences of disease experienced by the crop, presence of bare-soils due to damaged crop, are some of the comments, which might have helped in this context.

A critical assessment of our work may lead to expand the scale of work and need for a more extensive dataset to be considered. After sorting the database, we obtained only small number of fields for each class of sugarbeets.

Chapter 5 Conclusions and Future Work

5.1 Conclusion

SPOT image databases for the year 2002, on July 30, August 27 and September 16 were used to derive spectral characteristics of sugarbeet canopies in approximately 275 fields. The recoverable sugar content as an indicator of quality of sugarbeet for each field, was obtained from the field database of Southern Minnesota Beet Sugar Co-operative SMBSC), Renville-Minnesota. Four major classes of sugarbeets were analyzed. They were Mixed Rhizomania, Mixed Conventional, B3945 and B4811.

The first objective of this study to develop a paired data set representing whole-field canopy spectral characteristics from many fields from satellite image data, and whole-field measurements of sugarbeet quality was accomplished.

The second objective was to assess relationships between remotely sensed canopy spectral variations, using satellite images, with sugarbeet quality variation, and to test models to relate quality to canopy indices.

The trends of regression lines were meaningful in understanding variation of sugarbeet-harvest quality with change in canopy indices on two different single dates. The mixed class produced a significant link between changes in green NDVI over different time periods in the season.

Although the strengths of correlations were generally low, some models and time periods did produce statistically significant relationships. The following models were found to relate canopy parameters to recoverable sucrose concentrations.

- NDVI and fields of Mixed Rhizomania tolerant beets on a single July 30 image.

- SAVI and fields of Mixed Rhizomania tolerant beets on a single July 30 image.
- Green NDVI and a Mix of Conventional varieties on a single July 30 image.
- Change in NDVI for fields of Mixed Rhizomania tolerant varieties for the dates July 30 and September 16.
- Change in Green NDVI for a Mix of Conventional varieties between the dates of July 30 and August 27.
- Change in Green NDVI for a Mix of Conventional varieties between the dates of July 30 and September 16.
- Change in Green NDVI for variety B4811 between the dates of July 30 and August 27.
- Change in SAVI for variety B4811 between the dates of July 30 and August 27.
- Three parameter models using change in NDVI, Green NDVI and SAVI for time interval July to September for Mixed Conventional class.
- Six parameter model using changes in NDVI, Green NDVI and SAVI over two time intervals, from July to August and from August to September, for Mixed conventional class.
- Two parameter model using changes in Green NDVI from July to August and August to September.
- Six parameter model using changes in NDVI, Green NDVI and SAVI over two time intervals, from July to August and from August to September, for B4811 variety.

Models for temporal changes in index values generally associated a declining slope (change in index) with higher recoverable sucrose.

The findings suggest that sugarbeet canopy may be used to model recoverable sucrose concentration trends. However, the data results also indicate that additional information will be needed in the database to reduce the confounding effects of disease, weeds, and plant population variation on canopy models.

5.2 Scope for Future Work

The presented work confirms some needs. The first need is for an availability of relatively large database for each variety and the second need is for an enrichment of database with the additional information about the crop health. Human judgment is involved while decision is to be made to pick or skip a particular area under crop cultivation based on visual interpretation of the enlarged image. This decision can be supported by a set of comments and notes as additional information about the crop status in field, posted in the field database.

The future work will have a scope to satisfy these needs for the betterment of analysis and arrive at more consistent predictor models.

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